St. Petersburg University

Master in Management

Factors Influencing Adoption of Platform as a Service in Universities

Master's Thesis by the 2nd year student
Concentration — Information Technologies and Innovation Management
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ЗАЯВЛЕНИЕ О САМОСТОЯТЕЛЬНОМ ХАРАКТЕРЕ ВЫПОЛНЕНИЯ ВЫПУСКНОЙ КВАЛИФИКАЦИОННОЙ РАБОТЫ

Я, Ефремов Артем Сергеевич, студент второго курса магистратуры направления «Менеджмент», заявляю, что в моей ВКР на тему «Факторы, способствующие внедрению облачных сервисов PaaS в университетах», представленной в службу обеспечения программ магистратуры для последующей передачи в государственную аттестационную комиссию для публичной защиты, не содержится элементов плагиата.

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________________________________ (Подпись студента)

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I, Efremov Artem Sergeevich, second year master student, program «Management», state that my master thesis on the topic «Factors Influencing Adoption of Platform as a Service in Universities», which is presented to the Master Office to be submitted to the Official Defense Committee for the public defense, does not contain any elements of plagiarism.

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29.05.2017 (Date)

АННОТАЦИЯ

Автор	Ефремов Артем Сергеевич
Название ВКР	Факторы, способствующие внедрению облачных сервисов PaaS в университетах
Направление подготовки	Менеджмент
Год	2017
Научный руководитель	Кандидат технических наук, доцент Яблонский Сергей Александрович
Описание цели, задач и основных результатов	Целью исследования является выявление факторов, оказывающих влияние на использование студентами облачных платформ и наиболее известных технологий, предлагаемых платформами-лидерами: когнитивные вычисления, интернет вещей, “платформа как услуга”, продвинутые инструменты анализа данных. В результате обзора литературы, посвящённой новым технологиями и моделям принятия технологий, единая теория принятия и использования технологий (UTAUT) была выбрана базовой теоретической моделью для исследования. Исследовательские гипотезы были протестированы с помощью программного продукта IBM Watson Analytics, а также техники моделирования структурными уравнениями в IBM SPSS Amos, основываясь на данных, полученных в ходе опроса 150 студентов, обучающихся на математико-механическом факультете и факультете прикладной математики - процессов управления СПбГУ. Результаты исследования показывают, что желание студентов использовать платформу IBM Bluemix зависит, в основном, от их желания использовать когнитивные технологии (IBM Watson) и “платформу как услугу” (PaaS). В свою очередь, желание использовать эти технологии зависит напрямую от ощущаемой полезности и лёгкости использования и косвенно от влияния преподавателей и однокурсников. В общем, 56.2% респондентов продемонстрировали интерес к платформе IBM Bluemix, хотя всего несколько студентов использовали платформу ранее.
Ключевые слова	Принятие технологий, университет, UTAUT, цифровая платформа, когнитивные технологии, интернет вещей, облачные технологии, продвинутый анализ данных, платформа как услуга.

ABSTRACT

Master Student's Name	Efremov Artem Sergeevich
Master Thesis Title	Factors Influencing Adoption of Platform as a Service in Universities
Main field of study	Management
Year	2017
Academic Advisor's Name	Associate professor, Sergey A. Yablonsky
Description of the goal, tasks and main results	Goal of the study is to identify factors affecting adoption of digital computing platforms and most prominent services offered by the leading platforms: cognitive computing, Internet of Things, cloud computing, and advanced analytics among university students. To get a better understanding of the research area, review of the literature related to top emerging technologies and technology adoption theories was conducted. The multi-technology implementation of the unified theory of acceptance and use of technology (UTAUT) was selected as a basic theoretical model for the research. The research hypotheses were tested using IBM Watson predictive analytics software and structural equation modeling in IBM SPSS AMOS based on data which was gathered during survey from 150 bachelor, masters, and doctoral students studying at Saint Petersburg State University. Research findings suggest that students' intentions to use IBM Bluemix platform are affected by their intentions to use cognitive computing services and platform-as-a-service, while intentions to use these services are influenced directly by performance expectancy and effort expectancy and indirectly by social influence from university instructors and peers. Overall, 56.2 percent of respondents claimed that they would be interested to try IBM Bluemix, while only a few students had had a prior experience with the platform.
Keywords	Technology adoption, university, UTAUT, digital platform, cognitive computing, Internet of Things, cloud computing, advanced analytics, platform as a service

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INTRODUCTION

Cognitive computing, Internet of Things, and cloud computing were the hottest technologies during the last few years, and they are expected to have a significant impact on industry, academia, and society in the future. Overall, economic impact of these three technologies is estimated by McKinsey Global Institute to be as much as 9.6 trillion to 19.1 trillion US dollars annually in 2025.

By using digital computing platforms, which combine these technologies in one place, developers can create highly innovative applications by focusing their efforts and resources on value-adding features without dealing with extreme complexity of underlying technologies.

Adoption of digital computing platforms in universities can increase the educational and scientific results, as it allows students to quickly and economically access advanced technologies, gain a deeper understanding of these technologies, and better prepare them for their future career. Since the rise of cognitive computing and Internet of Things technologies will potentially reshape a job market, the IT students with knowledge of these technologies will be in high demand throughout the next decades.

However, so far, little attention has been paid by researchers to the factors influencing acceptance of digital computing platforms offering access to these technologies among university students. Hence, the objective of the study is to identify factors affecting adoption of emerging technologies in the university context, and statistically test the research hypothesis about the influence of those factors on the students' behavioral intentions to use these technologies for educational or professional purposes.

Potentially, results of the research can be used by digital platforms, such as IBM Bluemix, to adjust educational programs, which are offered to university students to familiarize them with new technologies, in order to increase a level of technology adoption among students.

The research object of the study is university. The research subject is factors affecting adoption among university students of four emerging technologies integrated in IBM Bluemix platform: cognitive computing, internet of things, cloud computing, advanced analytics.

The remainder of the study is structured as follows: the first chapter of this paper contains a review of emerging information technologies (with focus on such technologies as cognitive computing, internet of things, cloud computing, and interconnections between them) and technology adoption models with special attention paid to the application of these models in educational context.

As a result of the literature review, specifics of research object and subject are going to be determined, research gap is identified, and research questions are formulated.

Chapter 2 describes theoretical research model and research hypothesis, defines research approach, research strategy, and data collection methods, and describes quantitative methods used to test research hypothesis.

Chapter 3 contains description and assessment of results of the empirical research. The last chapter is devoted to the discussion of the results, description of theoretical and managerial implications, as well as limitations of the study.

1. LITERATURE REVIEW

The following chapter contains a review of the literature related to top emerging technologies and factors affecting their acceptance in various contexts. This chapter will help to identify the research gap and formulate research questions which will be answered in this research.

The first part of the chapter is devoted to top emerging technologies with special attention paid to such technologies as cloud computing, Internet of Things, and cognitive computing. The second part of the chapter describes and compares five popular technology adoption models: TAM, TPB, IDT, TOE, and UTAUT. The third part is focused on adoption of technologies described in the first part of the chapter. The fourth part describes different studies devoted to identification of factors influencing adoption of technologies in universities.

Finally, the research problem is specified and related research questions are formulated.

1.1 Emerging Technologies

According to the Gartner’s top strategic technology trends for 2016, a "digital mesh" keeps growing due to the constantly increasing number of interconnected devices, apps, information, and services which leads to merging of physical, virtual and electronic environments. Such devices as desktop computers, smartphones, sensors and actuators, wearable devices, smart home gadgets may interact with each other by connecting to back-end servers through various networks.

Amount of data produced by these devices continues to grow at exceptionally high rate. Such enormous amounts of diverse and noisy data being collected from multiple sources and stored at back-end servers require advanced data analysis technologies and approaches in order to extract more knowledge out of raw data and support interactions between various devices.

Furthermore, these huge amounts of data can be used for creating “smart” physical and software-based machines which are able not only execute a predefined set of commands, but also understand, learn, predict, adapt and potentially operate autonomously. By using advanced machine learning techniques (i.e., neural networks, deep learning, natural language processing), it is possible to create devices which are able to use sensory and contextual information in order to understand environment, as well as, learn, and change future behavior (Gartner 2015).

In turn, improvements in artificial intelligence and machine learning, decreasing cost of computational resources, and huge amounts of data drive further development of virtual personal assistants (i.e., Siri, Google Now, Microsoft Cortana), chatbots, smart home assistants (i.e., Amazon Alexa, Google Home), and intelligent things such as robots, autonomous vehicles, commercial unmanned aerial vehicles.

Moreover, advances in data analysis tools (i.e., image recognition, real time analytics) support development of immersive technologies, such as augmented and virtual reality which can be used in various contexts ranging from mobile games to education. One more related digital trend is digital twins, that is dynamic software model of a physical thing or system which allows analyzing and simulating work of products in real world conditions throughout the whole product lifecycle from design to utilization.

A fast-growing number of interconnected devices, as well as, huge amounts of data generated by them requires changes in existing technology architectures, usage of new approaches for development and operations, and shift from technical infrastructure to ecosystem-enabling digital platforms which are used for communicating, controlling, managing, and securing devices. According to Gartner's top strategic technology trends for 2017, platforms and services for Internet of Things, artificial intelligence and conversational systems will be a key focus for organizations in next three to five years.

1.1.1 Cognitive Computing

One of the most perspective technologies which can be used for processing data is cognitive computing, which can be defined as a set of technological capabilities such as machine learning, natural language processing, and high-performance computing.

According to IBM Institute for Business Value, the main difference between cognitive computing systems and traditional software systems is that cognitive-based systems are able to build knowledge and learn, understand human language, and reason and interact naturally with humans. In other words, cognitive computing technologies enable machines to do the tasks which previously could be performed only by humans: sense, learn, and act (Bataller & Harris 2015).

The forecasted spending on the artificial intelligence systems in 2017 will reach 12.5 billion dollars according to analysts from International Data Corporation (2017), while the compound annual growth rate for the future periods is expected to be as high as 54.4 percent through 2020. The largest area of spending in 2017 (36 percent) will be cognitive computing systems, which is expected to experience a dramatic annual growth of 69.6% during the next 5 years.

In 2025, as shown in the Figure 1, the global artificial intelligence market is expected to be worth approximately 36.8 billion dollars. Currently, major applications of artificial intelligence include image recognition, object identification, detection, and classification, as well as automated geophysical feature detection.

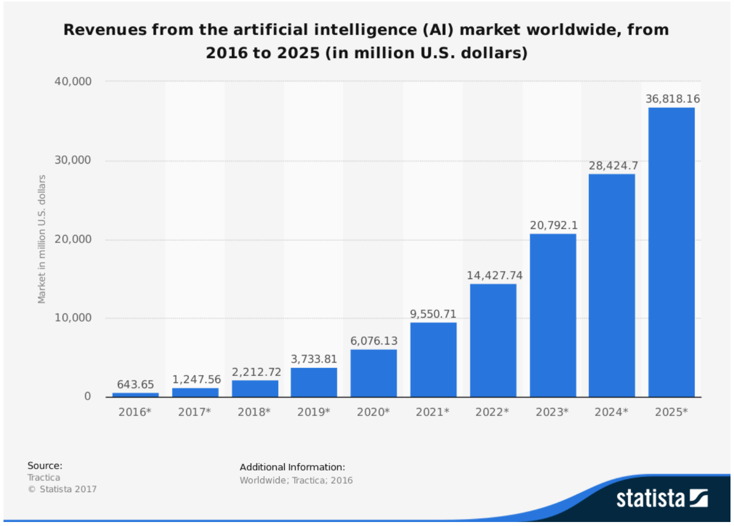

Figure 1: Revenues from the AI Market Worldwide (Tractica 2016)

In Russia, cognitive (neuro) technologies market is included in the list of key markets of Russian national technology initiative (NTI). Besides that, artificial intelligence and big data are considered as key technologies influencing NTI markets. According to the roadmap for “Neuronet”, the market size of Russian cognitive technologies market in 2016 is 4 billion rubles, and the target market size in 2020 is 44 billion of rubles (or 0.25 percent of worldwide market).

Economic impact of human work automation with help of cognitive computing technologies is estimated by McKinsey Global Institute to be as high as $5.2 trillion to $6.7 trillion annually by 2025. For example, development of natural user interfaces can fully automate work of customer support service or call center sales; machine-learning techniques can help managers to better monitor production processes, understand roots of the problems, or make accurate forecasts.

Actually, development of cognitive computing technologies is driven primarily by rapid growth of computing power of devices, advances in machine learning and big data processing, development of natural user interfaces (computer vision, natural language processing etc.), and widespread adoption of cloud computing among individuals and organizations.

Cognitive computing systems are able, through a machine learning technology, to adapt their behavior based on experience, rather than needing to have all the rules pre-programmed (Bataller & Harris 2015). By learning from vast amounts of structured and unstructured information, cognitive computing systems are able to develop deep understanding of the domain, discover connections in data, make data-driven decisions, and communicate output information to people in a timely, natural way.

Besides that, by using the data provided by “smart” machines, decision makers could get more timely access to reliable information, thus improving quality and speed of decision-making (Manyika et al. 2003). Recently, the head of Sberbank said that in five years 80% of all decisions would be made with help of artificial intelligence.

IBM Institute for Business Value claims that adoption rate of cognitive computing depends on various factors such as demand for more intelligent machines, expectations of cognitive computing, innovative policy issues, amounts of data available for analysis, development of related technologies, and availability of skilled data-scientists. One of the big concerns related to cognitive computing projects is difficulty in attracting the talent needed for the successful implementation of such projects.

Bataller and Harris (2015) say that the greater value from cognitive computing will come from understanding and integrating of related technologies. For example, advances in area of IoT will lead to better understanding of contexts, and, as a result higher quality of information available to cognitive systems.

1.1.2 Internet of Things

The Internet of Things (IoT) was one of the hottest technology topics during the last few years as it remains on the peak of inflated expectations for the third year in a row according to the Gartner’s hype cycle.

Cavalcante et al. (2016) describe IoT as a “concept relying on the interaction of smart objects with each other and with physical and/or virtual resources through the Internet”. The main elements of the IoT technology environment are sensors responsible for gathering information, network devices responsible for transferring collected data to the cloud, and software components responsible for managing information sent by sensors. Typical IoT application includes hardware components (sensors, actuators, MCUs, radio), networking components (gateways, routers), and software components (cloud computing servers, analytical platforms).

Currently, more than 9 billion devices are connected to the Internet. This number is forecasted to growth to 20 billion devices by 2020 and to 50 billion devices by 2025 (Bradley, Barbier, & Handler 2013).

The number of connected devices in Russia in 2016 was estimated by AC&M Consulting to be more than 10 million, and the annual growth rate for future periods is forecasted to be between thirty and forty percent.

According to the a roadmap for development of Internet of Things in Russia developed by Russian Ministry of Industry and Trade in cooperation with The Internet Initiatives Development

Fund, the number of connected devices in Russia in 2016 was equal to 16 million, while the target value for this indicator by 2020 is 320 million.

In 2017, the overall size of the global IoT market is calculated to be more than one trillion U.S. dollars. The estimated economic impact of the Internet of Things is between $2.7 trillion to $6.2 trillion annually by 2025 according to the study of McKinsey Global Institute (2013).

According to AC&M Consulting's report (2017), size of the IoT market in Russian in 2016 had grown by 42% and reached $1.2 billion. Currently, the biggest part of the market (57.6 percent) belongs to the developers of IoT applications and system integrators, while network infrastructure operators have less than 10 percent of the market.

The forecast of Russian IoT market by IDC (2016) predicts that there will be an average annual market growth of 21.3% between 2016 and 2020, and the market size will exceed 9 billion US dollars by the end of period.

The verticals with the biggest spending on IoT in Russia are manufacturing, transportation, and utilities. Such structure corresponds with worldwide spending on IoT which is shown in Figure 2 below.

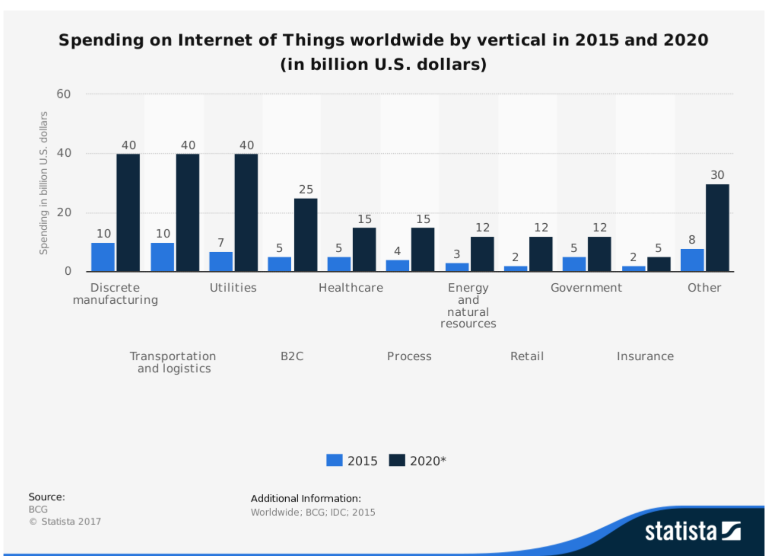

Figure 2: Spending on IoT Worldwide by Verticals (BCG 2015)

IoT success is driven by a mix of various technologies ranging from low-cost development boards to cloud computing and machine learning. Another driver of IoT is declining cost of computing, storage, and networking.

TDWI study (2016) of IoT readiness shows that majority of organizations participating in the TDWI‘s study assume that IoT can provide value for them by increasing operational efficiency and offering new products and services to customers. However, at the same time, less than twenty percent of responders use IoT today.

The Internet of Things is still at early stages of adoption, but it can already be used to create value in various contexts. Texas Instruments have identified six key markets for the IoT with potential for exponential growth, they are building & home automation, smart cities, automotive, wearables, healthcare, and smart manufacturing (referred as Industrial Internet of Things). Usage of IoT in industrial context includes predictive maintenance and support, product design, optimization, asset monitoring and analysis, and customer analytics (TDWI 2016).

Merging of the IoT paradigm with cloud computing is primarily driven by the need of IoT infrastructure and applications to be improved in terms of computational resources, scalability, and performance. However, there are some challenges related to the integration of IoT and cloud computing, such as interoperability; security in terms of data integrity and confidentiality; lack of standardization; device orchestration; dealing with real-time data; and energy efficiency (Cavalcante et al. 2016).

1.1.3 Cloud Computing

Cloud computing, has become an integral part of information technologies a while ago, but it still serves as a basis technology for majority of emerging technologies described in the previous section. Cloud computing allows to collect, process, store, and analyze data from various endpoints, and provide access to computational resources to different stakeholders.

According to National Institute of Standards and Technology (2011), cloud computing is “a model for enabling convenient, on-demand network access to a shared pool of configurable computing resources that can be rapidly provisioned and released with minimal management effort or service provider interaction”. Wu (2011) suggests additional characteristics of cloud computing, such as on-demand self-service, ubiquitous network access, location independent resource pooling, rapid elasticity, and measured service.

There are three standard service models for cloud varying by the level of abstraction:

— Infrastructure as a Service (IaaS) provides remote virtual servers, operating systems, storage and network access but no software or application environment (Fanning & Centers 2012).

— Platform as a Service (PaaS) provides the entire infrastructure needed to run applications over the Internet (Pardeshi 2014). The user does not manage or control the infrastructure including operating systems, network, servers, or storage, but has full control over the deployed applications and hosting environment configurations (Choudhary & Singh 2015).

— Software as a Service (SaaS) provides the application which runs and interacts through Internet (Pardeshi 2014) and user does not control the basic cloud infrastructure including servers, network, operating systems, and storage. SaaS appears to be the most widely used cloud service model.

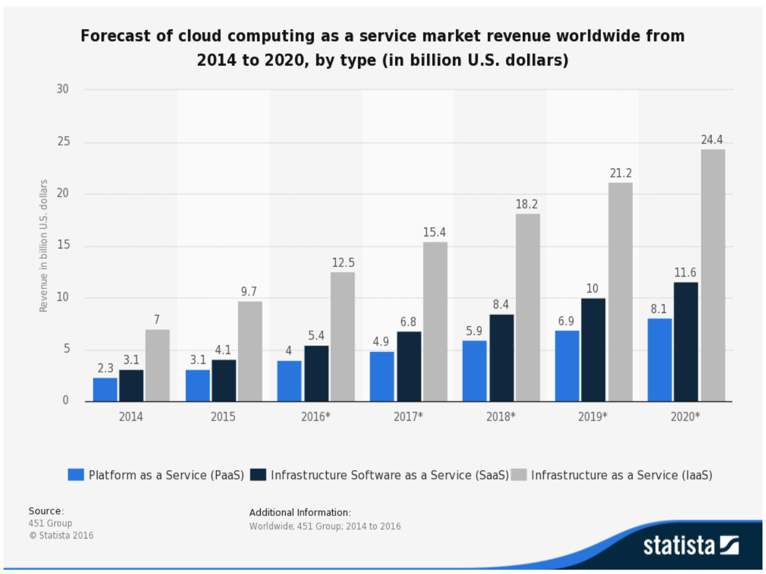

Figure 3: Forecast of Cloud Computing Revenues (451 Group 2016)

A forecast of revenue from the cloud computing is shown in Figure 3 demonstrates the steady growth of revenues among all cloud computing service models, with IaaS being the leader with around 15 billion dollars in 2017.

Analysis of Russian cloud computing market conducted by SAP Russia and Forester (2017) shows that in 2016 the market size was equal to 22.6 billion rubles (annual growth rate - 43%). The forecasted market size in 2020 is 48.3 billion rubles (0.4 percent of worldwide market) with average annual growth rate between 2016 and 2020 equal to 20.9 percent.

Besides that, there are four deployment models for cloud services: private cloud, public cloud, hybrid cloud, and community cloud (Pardeshi 2014). Public clouds are owned and managed by cloud providers and their main feature is that the infrastructure and computational resources can be accessed through the Internet. Contrary, a private cloud is a deployment model that maintains the computing environment only for one organization where organizational users can share the infrastructure resources. (Jansen & Grance 2011). In community model, the infrastructure is shared by different organizations which have common concerns, and hybrid cloud assumes that some part of computing environment is managed by organization and another part is managed by cloud provider.

Benefits of cloud computing are mobility that is ability to use service from mobile devices, flexibility (Pardeshi 2014) because it provides fast and easy deploys, payment model where you pay only for what you use, access to new services which always offer the latest functionality, absence of initial investments in hardware and software, better performance and lower fixed costs as a result of decreased need in in-house IT staff and data centers, ability to easily share systems with partners (Wu et al. 2011), elasticity as it transfers the risks of resource over-provisioning and under-provisioning to cloud providers.

Although benefits of cloud computing are well known, organizations are still cautious about the risks associated with cloud services such as data protection, loss of direct control of resources and software, risk and non-performance issues, organizational support and acceptance, network related issues, contractual and jurisdictional issues (Pardeshi 2014). Alharbi (2014) emphasizes that security and trust are considered as the main barriers preventing organizations from adopting cloud solutions.

1.1.4 PaaS as a Basic Delivery Model of Cognitive Computing Services

According to the definition from NIST, platform-as-a-service (PaaS) is “the model to enable convenient and on-demand network access to a shared pool of configurable computing resources, such as compute, storage and network that can be provisioned rapidly and released with minimal management effort.” PaaS provides all required resources for custom software while maintaining the underlying IT infrastructure. PaaS solutions also support vertical and horizontal scaling capabilities (Kriz 2014).

Size of the global PaaS market is forecasted to reach 7.5 billion dollars by 2020 with an average annual growth of 20.9% according to the Global Industry Analysts (2015).

Two main benefits of using PaaS are cost benefits and faster development and deployment cycles. PaaS provides development teams this flexibility, while allowing service management teams managing infrastructure more efficiently (Daya & Shahir 2015). PaaS model supports the concept of rapid design, development, test, and new deployment.

By adoption PaaS, organizations can redirect the costs from maintaining the infrastructure to creating applications that provide real business value. Besides that, moving the application to the cloud platform simplifies the firm's IT structure. Additionally, since the application environment provides well-tested technologies and tools, it can decrease the risks and costs of application development (Fanning & Centers 2012).

Normally, cloud-computing platforms provide not only computing infrastructure, but also some additional digital services such as cognitive computing services, analytical services, IoT services.

For example, all major vendors offering PaaS solutions, such as IBM, Google, Microsoft, HP, and Amazon, also provide cognitive computing services (see Table 1). By integrating cognitive computing services into cloud computing platforms, their customers are able to focus on development of new applications without spending resources on development of cognitive computing technologies and supporting complex infrastructure.

Table 1: Cognitive Products by Providers

Vendors	***Microsoft***	***HP***	***Amazon***	***Google***	***IBM***
Platform	Microsoft Azure	HPE Haven OnDemand	Amazon Web Services	Google Cloud Platform	IBM Bluemix
Products	Microsoft cognitive services	Audio-video, image analysis, text analysis, search APIs	Lex, Polly, Rekognition	Natural Languages API, Speech API, Translation API, Vision API	Watson

In general, all cognitive computing services offered by these platforms can be categorized into five groups called "Vision", "Language", "Speech", and "Knowledge".

Services from "Vision" group are used to understand content of images and video - find human faces and other objects, detect text, classify images and moderate them. Language cognitive services are used to process written text - categorize the intent behind text; extract concepts, entities, keywords, categories, relations; understand emotional context; detect text's language and translate text into one or more languages. Text cognitive computing services primarily relate to the conversion of speech to text and vice versa, as well as, speaker's identification and verification by voice. Knowledge services relate to extraction of insight from data sets.

Summary of the services offered by major cloud computing platforms is represented in the Table 2. In addition to the services represented in the table, each provider offers some unique cognitive services. For example, Microsoft cognitive services allow developers to create Q&A systems; HP's HavenOnDemand platform offers visual recognition of license plates; Google Cloud allows detecting changes of scenes in video; and IBM Watson allows extracting personality insights based on based on how a person writes.

Table 2: Cognitive Services by Providers

Service	***Microsoft***	***HP***	***Amazon***	***Google***	***IBM***
Vision					
Image classification	+	+	+	+	+
Image search	+	-	+	+	+
Optical character recognition	+	+	-	+	-
Emotion recognition	+	-	+	-	
Content moderation	+	-	+	+	-
Face detection	+	+	+	+	+
Face verification	+	-	+	-	-
Landmark detection	+	+	+	+	-
Language					
Text understanding	+	+	+	+	+
Sentiment analysis	+	+	-	+	+
Translation	+	-	-	+	+
Language detection	+	+	-	-	+
Chatbots creation	+	-	+	-	+
Syntax Analysis	+	+	-	+	+
Speech					
Speech to text	+	+	+	+	+
Text to speech	+	-	+	+	+
Speaker Verification	+	-	-	+	-
Knowledge					
Natural language queries	+	+	+	+	+

As the Table 2 shows, Microsoft provides the greatest number of services related to computer vision, while Amazon and Google take the second place in terms of number of “vision” services. As for the “Language” and “Speech” cognitive services, Microsoft, Google, and IBM are leaders.

Development of IoT-related applications which normally include a big number of interactions between various endpoints operating in unpredictable context where decisions have to be made in a very short period requires efficient and reliable ICT infrastructure. Such infrastructure, along with additional services and integrations, can be offered on-demand by digital computing platforms.

According to Gartner's predictions for PaaS market (2015), more than half of new applications developed on PaaS in next 3 years will be related to the Internet of Things. Revenue forecast of third-party digital platforms offering IoT services is shown in the Figure 4 below.

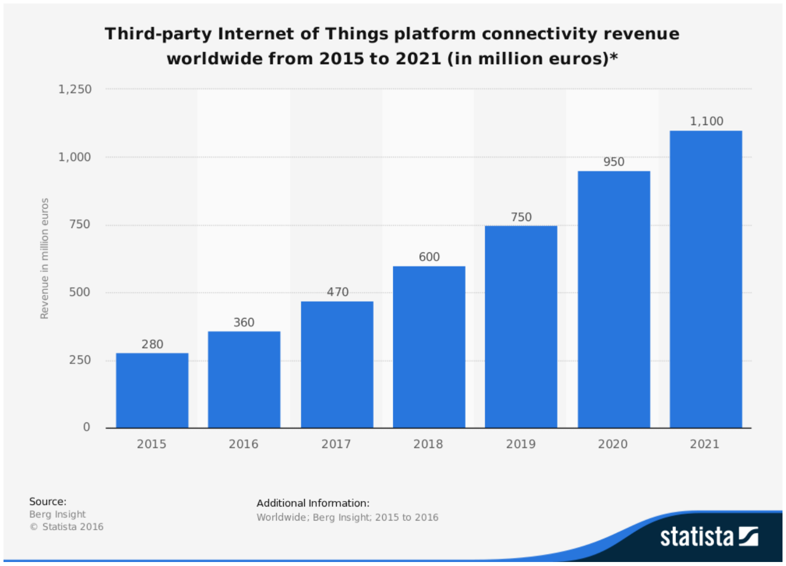

Figure 4: Third-party IoT Platform Connectivity Revenue Worldwide (Berg Insight 2015)

Forecasting the potential benefits brought by cloud computing to IoT, major cloud vendors started offering cloud services aiming to support IoT applications in terms of computing capabilities, data analytics, resource elasticity, and scalability (see Table 3).

Table 3: IoT Solutions by Providers

Vendors	***Microsoft***	***HP***	***Amazon***	***Google***	***IBM***
Platform	Microsoft Azure	HPE Haven OnDemand	Amazon Web Services	Google Cloud Platform	IBM Bluemix
Products	Azure IoT Suite	HPE Universal IoT Platform	AWS IoT Platform	IOT solutions	IBM Watson IoT

The main objective of the digital platforms which integrate IoT and cloud computing paradigms is to allow integrating, managing, and monitoring connected devices at real-time. In these platforms, the amount of cloud resources required to support the integrated devices is provided on-demand. They also support the development of IOT applications by providing APIs for data storage, data retrieval and analysis, and deployment and execution of applications. In addition, there are other relevant features offered by some platforms in the selected studies, such as support for the orchestration of devices and sharing of virtualized IoT devices.

Distribution of computing platforms used in IoT projects is depicted in the Figure 5 shows that majority of survey respondents used AWS IoT platform and private clouds for developing Internet of Things solutions. Microsoft Azure is the third most popular choice, while Google cloud platform and IBM Bluemix share the fourth and five places. Seventeen percent of respondents do not use any cloud platforms for development of IoT projects.

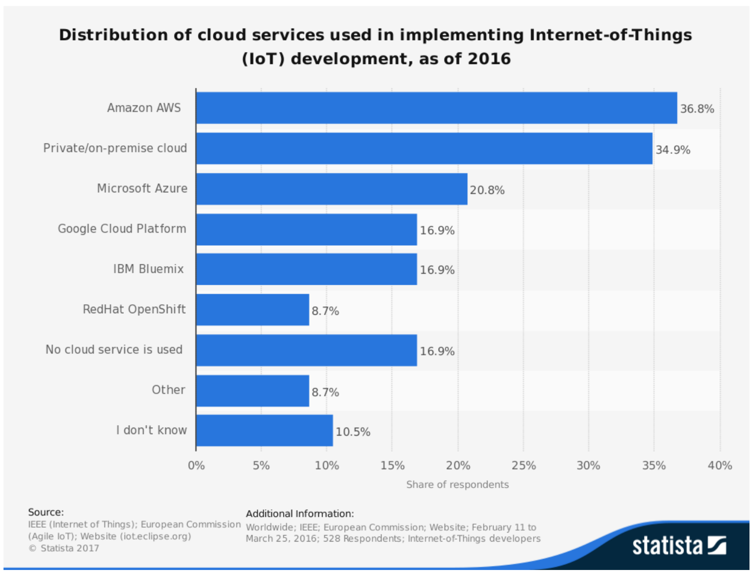

Figure 5: Distribution of Cloud Services Used in IoT Projects (IEEE 2016)

1.1.6 IBM Bluemix Technological Stack

IBM Bluemix is a PaaS developed by IBM which “supports several programming languages and services as well as integrated DevOps to build, run, deploy and manage applications on the cloud.” The IBM Bluemix cloud platform allows developers to integrate high-performance cloud infrastructure and cutting-edge services into their development environment.

According to the research of Enterprise Strategy Group (2016), IBM Bluemix is one of top four cloud computing platforms (AWS, Microsoft Azure, Bluemix, Google Cloud Platform) with adoption growth rate which is 5 times higher than average growth rate of the other PaaS market leaders. In 2016, the number of developers using Bluemix increased, on average, by 20 thousand people each week. IBM’s total annual revenue (June 2015 - June 2016) from cloud services was equal to $11.6 billion.

Infrastructure offered by Bluemix includes computing resources (bare-metal and virtual servers) which can be customized based on customers' workload requirements, in terms of, processing power, RAM size, SSD disk volume, and operating system; networking services; storage services; security services; DevOps and so on. IBM Bluemix is offered in three deployment models (public cloud, private cloud, and local) or any combination of them.

IBM Bluemix platform offers a constantly growing number of cutting-edge services and APIs, most famous of which are Watson Analytics, IoT platform, Data and analytics, and Bluemix mobile.

Watson Analytics is a cognitive computing system which can be easily integrated with other applications. In more detail, it can be described as a "smart data discovery service available on the cloud which guides data exploration, automates predictive analytics and enables effortless dashboard and infographic creation" (Almutairi & El Rahman 2016).

Watson analytics provides customers with such services as data processing, data analysis, and visualization. With help of Watson, developers can use such technologies as visual recognition, speech to text, natural language classification, just to name a few. Besides that, Watson analytics can also be used for predictive analytics and in applications that manage big data, it also enables performing analytics on data in order to make complex decisions, and fosters interaction between machines and persons through natural language.

With help of Bluemix IoT platform developers can easily connect devices to the cloud and securely exchange data with the platform through REST and real-time APIs, which can be later interpret with help of Bluemix apps or developers' own services. For example, IBM Watson IoT Context Mapping service can be used for analysis of moving object trajectories by leveraging road network-based geospatial services.

Date generated by the application can be stored in various relational and non-relational databases, merged with third-party data (for example, data from weather company service), and analyzed by different advanced analytics tools to answer questions or solve problems. Advanced analytics can be defined as a set of analytical applications that helps to turn low-level data into high-level knowledge by extracting patterns or models from observed data (Bose 2009). In 2015, IBM Watson analytics had 12.7% market share being the second largest vendor on advanced and predictive analytics software market (SAS Institute 2015).

The Mobile Cloud Services can be used for accelerating Android, IOS, and web mobile app development by providing data and file storage, application authentication, push notifications, and server-side application logic.

By using digital computing platforms, such as IBM Bluemix, developers can create sophisticated applications by taking advantages from synergy effect provided by combining such cutting-edge technologies as cloud computing, cognitive computing, and IoT technologies; and focusing on development of value-adding features without dealing with extreme complexity of underlying technologies.

1.2 Technology Adoption Theories

The concept of technology adoption was suggested by Rogers (1995) and it can be defined as “a decision to make full use of an innovation as the best course of action available”. According to Rogers (1995), the adoption process consists of following stages: knowledge of an innovation, forming an attitude, decision to adopt or reject, implementation, and confirmation of this decision.

The technology adoption has been an important topic in information systems research for a while. Since 1960s, substantial research has been done aimed at identification of factors affecting technology acceptance. With increasing complexity of technologies, the constructs used in technology acceptance models shifted from solely technology-related to more context-related (Venkatesh 2006).

According to Oliveira and Martins’ (2011) literature review of technology adoption models, the most popular technology adoption models are

- Theory of Planned Behavior (TPB);
- Technology Acceptance Model (TAM);
- Diffusion of Innovations (DOI);
- Technology-Organization-Environment (TOE);
- Unified Theory of Acceptance and Use of Technology (UTAUT).

1.2.1 Theory of Planned Behavior

The Theory of Planned Behavior (Ajzen 1991) is an extension of the Theory of Reasoned Action (TRA). TRA claims that individual‘s behavioral intention can be considered as a function person‘s attitude toward performing the behavior, and a person‘s subjective norm regarding the behavior where attitude can be defined as “an individual's positive or negative feelings about performing the target behavior” and social influence is defined as “the person's perception that most people who are important to him think he should or should not perform the behavior in question” (Fishbein and Ajzen 1975).

TPB extended TRA by adding the construct of perceived behavioral control (PBC) which is theorized to be an additional predictor of intention and behavior (see Figure 6). Even if users have a strong intention to perform a behavior, they will not be able to do so without the necessary resources and skills. So, PBC can be defined as “perceptions of internal and external constraints of behavior” (Venkatesh et al. 2003).

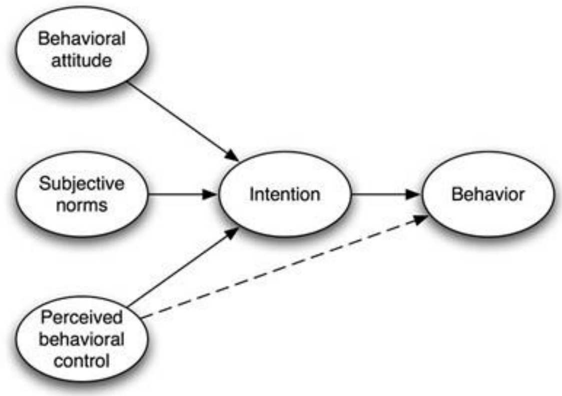

Figure 6: Theory of Planned Behavior (Ajzen 1991)

TPB has been successfully applied to the understanding of individual acceptance and usage of various technologies.

1.2.2 Technology Acceptance Model

TAM was developed by Davis (1989) and it was based on theory of reasoned action (TRA). TAM suggests that two core constructs that affect user attitudes and intentions in adopting a technology system are perceived usefulness (PU) and perceived ease-of-use (PEOU). PU is defined by Davis (1989) as "the degree to which a person believes that using a particular system would enhance his/her job performance" and PEOU as "the degree to which a person believes that using a particular system would be free of physical and mental effort”. Determinants of perceived usefulness and perceived ease of use are individual differences, system characteristics, social influence, and facilitating conditions (Armbrust et al. 2010).

The structural model of TAM is shown in Figure 7.

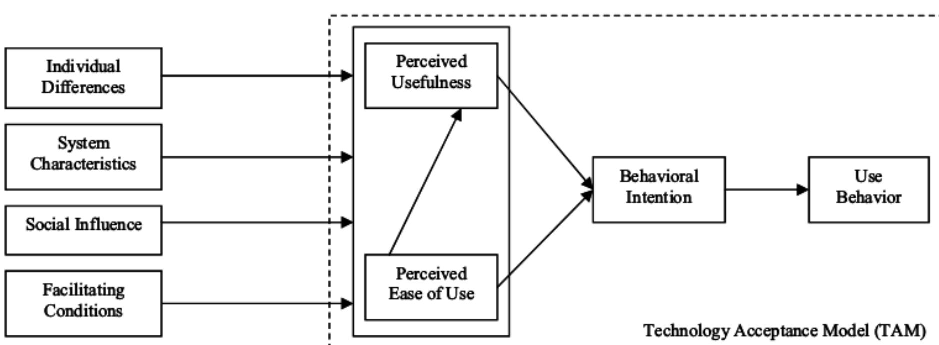

Figure 7: Technology Acceptance Model (Davis 1989)

Prior research using TAM has focused on three areas: some studies focused on the psychometric aspects of TAM constructs. Other studies provided assessment of the relative importance of TAM variables. Finally, some studies extended TAM by adding new determinants of behavioral intention and use behavior (Venkatesh et al. 2008).

Venkatesh and Davis (2000) claim that TAM consistently explains about 40% of the variance in usage intentions and behavior, that is TAM can be considered more reliable theory than alternative models such as TRA and TPB.

However, during the last three decades, the model was heavily criticized for some reasons. For instance, Venkatesh and Bala (2008) says that the model does not provide actionable guidance to practitioner. Lopez-Nicolas et al. (2008) notes that original TAM does not account for social influence and specifics of the analyzed technology. Wu (2011) supposes that TAM fail to address certain crucial issues such as security and trust, as well as marketing effort.

To address some of the above-mentioned problems, Venkatesh and Davis (2000) proposed an extension of TAM called TAM2 which identifies general determinants of perceived usefulness. According to Liu (2010), the model incorporates additional theoretical constructs such as social influence processes (subjective norm, voluntariness, and image) and cognitive instrumental processes (job relevance, output quality, result demonstrability, and perceived ease of use).

TAM3 model (Venkatesh and Bala 2008) was developed by combining TAM2 and the model of the determinants of perceived ease of use (Venkatesh 2000). The main difference of this model compared with the previous version is that TAM3 does not have any cross-over effects, so the determinants of perceived usefulness do not influence perceived ease of use and the determinants of perceived ease of use do not influence perceived usefulness.

Some researches argue that since TAM does not consider external factors besides perceived usefulness and perceived ease of use, it is more appropriate for research environments with the voluntary use of a technology, what is why TAM may be not suitable theory for this study.

1.2.3 Innovation Diffusion Theory

Another core theory in the field of technology adoption is Innovation Diffusion Theory (IDT) proposed by Rogers (1995). Diffusion is "the process by which an innovation is communicated through certain channels over time among the members of a social system" (Rogers, 2010). A common problem for majority of innovators is how to increase the rate of diffusion of new product or service.

The key elements in diffusion research are innovation, adopters, communication channels, time, and social system. IDT describes attributes of an innovation which have an effect on intent to adopt new technology and on how social context can influence the willingness to adopt. According to IDT, the six main factors that affect the process of diffusion of innovation within an organization, they are relative advantage, compatibility, complexity, trialability, observability, and ability to communicate product's benefits (see Figure 8).

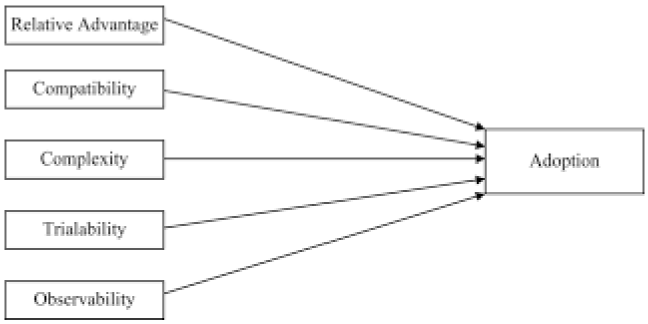

Figure 8: Adoption Factors in Diffusion of Innovation Theory (Rogers 1995)

According to Rogers, decision about innovation adoption is a process consisting of five stages: knowledge, persuasion, decision, implementation, and confirmation. At the first stage individual is exposed to an innovation, but he does not have information about the innovation. At the persuasion stage, individual becomes interested in the innovation and actively looks for related information. After that, individual makes a decision to accept or reject innovation based on its pros and cons. During the implementation stage individual determines actual usefulness of the innovation and may search for additional information. Finally, individual makes a decision to continue or discontinue usage of the technolpogy.

Lopez-Nicolas et al. (2008) developed a model which integrates TAM with Innovation Diffusion Theory (TAM-DTM), as he consider that “TAM and its modified versions are too parsimonious, incomplete, and tautological”. The model contains eight constructs including media influence, social influence, perceived flexibility, perceived status, attitude toward innovations, perceived usefulness, perceived ease of use, and behavioral intentions. The objective of the study was to evaluate the impact of different determinants on BI in the adoption of advanced mobile services. The analysis showed that traditional antecedents of behavioral intention, ease of use and perceived usefulness, could be linked to diffusion-related variables, such as social influence and perceived benefits.

1.2.4 Technology-Organization-Environment Framework

Depietro et al.'s (1990) Technology-Organization-Environment (TOE) framework emphasizes the role of contextual factors in the technology adoption process, and it groups these factors into three categories: technology, organization on the adopter side, and environment where adoption happens. Authors of the framework argued that any process technology adoption is affected not only by the technological context, but also by the organizational and environmental context.

The technology context refers to the internal and external technologies relevant to the firm. The organization context refers to the descriptive measures of the organization, such as its scope and size, and it relates to influence of organizational size, culture, and structure influential to the technology adoption. The environment context relates to the limitation and opportunities for a new technology, such as industrial segment, competitors, and government. (Martins et al. 2016). Structural model for the TOE framework is represented in Figure 9.

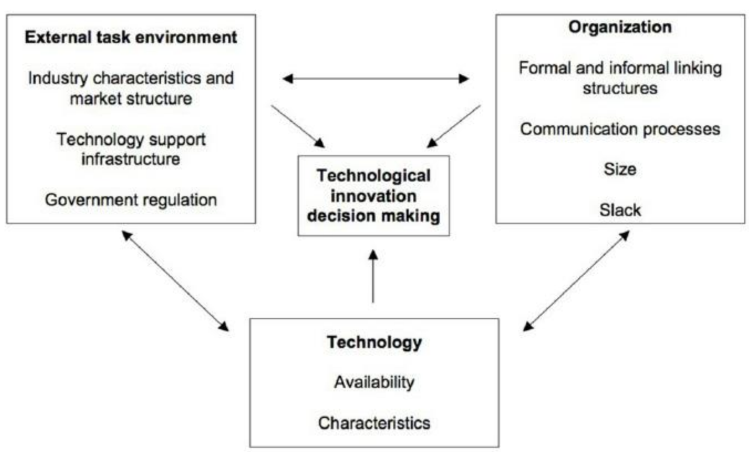

Figure 9: TOE Framework (Depietro et al. 1990)

Apart from IDT, TOE highlights the organizational factors of innovation adoption. One of the main advantages of the framework is that researchers may choose different technological, organizational and environmental factors for different IT innovations (Yang et al. 2015). However, the model was criticized for various reasons: Bose and Luo (2011) argue that it does not provide a concrete model for describing the factors that influence the organizational adoption decision, but instead provides a taxonomy of adoption factors; Martins et al. (2016) say that TOE framework does not take into consideration key factors such as cost savings and security concerns, which are important to the firm's adoption of technology.

1.2.5 Unified Theory of Acceptance and Use of Technology

Unified Theory of Acceptance and Use of Technology (UTAUT), proposed and validated by Venkatesh et al. (2003), integrated eight models, including TRA, TAM, the Motivational Model, TPB, TAM and TPB combined, the model of PC utilization, IDT and the social cognitive theory (Lin et al. 2013).

Originally, UTAUT was created for explaining the factors affecting technology adoption by employees. UTAUT includes four core determinants which are performance expectancy, effort expectancy, social influence and facilitating conditions in addition to four control variables which are gender, age, experience, and voluntariness of use (Alharbi 2014).

The UTAUT constructs are based on the similar variables from other technology adoption theories and models. Performance expectancy is similar to relative advantage from IDT and perceived usefulness from TAM. Effort expectancy is similar to ease of use from IDT and perceived ease of use from TAM. Social influence is similar to subjective norm in TAM2 and image in IDT. Facilitating conditions are similar to perceived behavioral control from TPB and compatibility from IDT.

According to UTAUT, performance expectancy, effort expectancy, and social influence are theorized to influence behavioral intention to use a technology, while behavioral intention and facilitating conditions determine technology use (Venkatesh et al. 2012). Behavioral intention is one of the main dependent variables of the UTAUT model and it is defined as the degree to which a person formulate a mindful plan to perform specific future behavior. The structural model for UTAUT is represented in the Figure 10 below.

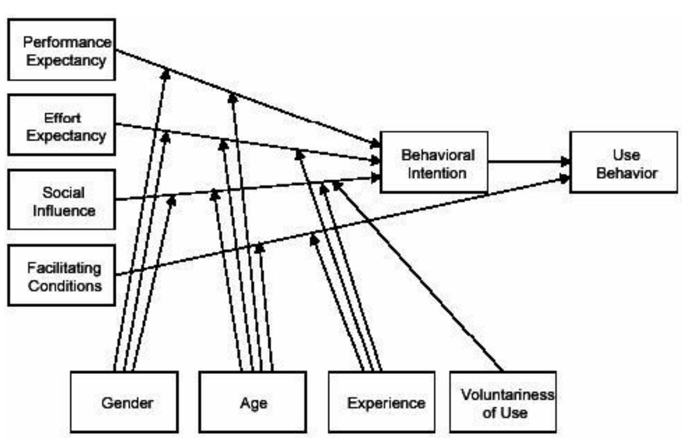

Figure 10: Unified Theory of Acceptance and Use of Technology (Venkatesh et al. 2003)

Alharbi (2014) say that UTAUT provides better understanding of the technology adoption process than any other model included in UTAUT. The UTAUT model demonstrated up to 70% accuracy at predicting user acceptance of information technology innovations, which is significantly higher than the prior models (Lin et al., 2013). The model has been validated for the acceptance the technology in various settings, among them: healthcare system, education, mobile commerce, just to name a few (Alharbi 2014).

However, some researchers criticized the model for a few reasons. Yoo et al. (2012) notes that most previous studies were conducted among students or university instructors; predictability of UTAUT might vary when applied in different cultural setting because most previous researches were conducted in developed western countries; it is unclear whether intrinsic motivators and extrinsic motivators influence adoption levels differently. Besides that, Yoo et al. (2012) also emphasize that considering the big number of variables involved in UTAUT, it is not economical for organizations to address all of them in order to promote the acceptance of new technologies among employees.

To improve the explanatory power of UTAUT, several studies proposed to extend it by adding constructs which are relevant to specific context of the research. Frequently used constructs include demographic and situational variables, cognitive variables and personality-related variables (Lin et al. 2013).

Venkatesh, Thong, and Xu (2012) summarize that there are three broad types of UTAUT extensions. The first type of extension examined UTAUT in new contexts, such as new technologies, new user populations, and new cultural settings. The second type is the addition of new constructs in order to broaden the scope of the model. The third type is the inclusion of external predictors of the UTAUT variables.

In 2013, Taiwo and Downe used meta-analysis in his study in order to investigate the validity of UTAUT and reveal how much this validity is substantiated in present literature. The largest effect size in the study was between performance expectancy and behavioral intention, it means that the ability of the system to assist users to achieve task quickly will increase adoption rate. Taiwo's research confirmed the influence of effort expectancy to behavioral intention; it means that complex system interface makes users less interested in using the system. Results of the research showed that the effect size of behavioral intention and use behavior turned out to be small, though it might be caused by the inability of most studies to measure the actual usage of technologies.

In 2013, Venkatesh et al. developed UTAUT2 model: the UTAUT extension in a consumer use setting. UTAUT2 includes not only the relationships from UTAUT, but also adds new constructs and relationships that improve the applicability of UTAUT to the consumer context. To modify UTAUT for the consumer technology acceptance and use context two drivers (hedonic motivation and price value) are included in UTAUT2. Another major theoretical contribution of this work is in the integration of habit into UTAUT. Venkatesh et al. (2013) emphasizes several managerial implications of the study. It suggests that the price value of IT applications can influence consumers' technology use, that there is a significant impact of consumers' habit on personal technology use, and that different cohorts of consumers attach different weights to various factors that influence their technology use.

Technology acceptance and usage was one of the most popular topic in information systems research for a while. In order to identify factors affecting adoption of new technologies various models and frameworks has been suggested, some of them, namely, TPB, TAM, IDT, TOE, and UTAUT were described in this section. The choice of particular model depends on various factors such as technology in question, context, researcher's resources and competences.

1.3 Multidimensional Adoption

The benefits and potentials of adopting cognitive computing, cloud computing, and IoT services and applications are well documented in the literature. Although, adopting such technologies is still facing various challenges (Alharbi, 2014).

1.3.1 Cognitive Computing Adoption

A recent research conducted by the National Business Research Institute claims that 38% of big companies are already using cognitive computing technologies and 62% plat to use them 2018. The research also emphases that the most widespread applications of the cognitive computing are predictive analytics and automation of simple and repetitive tasks.

While the topic of cognitive computing services is quite new, some research aimed to identification of factors influencing adoption of big data analytics (BDA), machine learning (ML), and artificial intelligence (AI) have been conducted.

TDWI research (2016) related to big data adoptions claims that only 10% of deployed a special solution for managing big data (and only 3% are relative mature), and another 10% of respondents said they have been developing a big data management solution.

Angrawal (2015) applied TOE framework to identify predictors of BDA adoption in China and India. Results of the research showed that such variable as compatibility, organizational size, competition intensity, and environmental uncertainty had positive influence on organizations' intention to adopt BDA, while regulatory support and complexity were found to have negative effect on behavioral intention. Surprisingly, relative advantage and technological competence were found to be insignificant predictors of BDA adoption.

Result of another study related to BDA adoption (Kang & Kim 2015) where TOE framework was used also demonstrated that perceived and direct benefit was not significant determinants of BDA adoption. Among factors which affected the process of BDA adoption significantly were IS competence, industrial pressure, and financial readiness.

Results of the research of determinants of BI adoption in organization conducted by Malladi and Krishnan (2013) are consistent with factors affecting BDA adoption which were identified in previously mentioned studies. According to the research, the process of adoption of BI depends on such factors as technological readiness, organizational size, compatibility with firm's business processes, and competitive intensity.

Apart from the previous researchers, Soon, Lee, and Boursier (2016) applied a modified TAM for identification of determinants affecting Big Data adoption. The most important predictors of Big Data adoption were found to be perceived usefulness, perceived benefit, and perceived risk, while effect of perceived ease of use was found insignificant.

1.3.2 IoT Adoption

Identification of critical factors for IoT adoption allows managers to focus on these critical factors and increase the rate of IoT adoption. However, a review of the literature related to adoption of IoT services made by Al-Momani et al. (2016) showed that research in this field are still in infancy.

Gao and Bai's (2014) used a modified TAM model in order to identify factors influencing acceptance of IoT technology. The results of the empirical study showed strong influence of such factors as perceived usefulness, perceived ease of use, social influence, perceived enjoyment, and perceived behavioral control on behavioral intention to use IoT services. Besides that, in accordance to TAM, perceived ease of use were found to influence perceived usefulness.

Mital et al. (2016) also used a modified TAM model for exploring the intention to use IoT devices. The results showed that both TAM's constructs have significant and strong influence on respondents' intentions to use IoT devices. The effect of perceived ease of use was found to be stronger than effect of perceived usefulness.

Other researchers (Lin et al. 2016) used TOE framework to develop a model of IoT adoption in Chinese agricultural supply chain. The model includes 12 factors distributed by three TOE's dimension, but the model has not been tested so far.

Finally, Al-Momani et al. (2016) created a framework of the adoption of IoT services which is based on variables used in related researches and theoretical concepts from TAM and UTAUT models. The framework consists of seven independent variables (usefulness, ease of use, social influence, cost, IT knowledge, trust, security & privacy) which are theorized to affect the behavioral intention which in turn is expected to affect the use behavior.

1.3.3 Cloud Computing Adoption

Although cloud computing is an emerging technology, a considerable empirical research has been conducted concerning the factors affecting cloud computing adoption by organizations.

In 2011, Wu used TAM-DTM model in order to develop an explorative model that examines important factors affecting SaaS adoption. The author considered specifics of SaaS and added two crucial constructs, namely, Marketing Efforts as well as Security and Trust. The key finding of the research was that Social Influence is the factor which affects most of the determinants of behavioral intentions to use SaaS. SaaS adoption could also be influenced by a set of factors such as an organization's characteristics and competitive strategies, influences of internal and external parties on the adoption decision process, perceived benefits of the new technology, and organizational readiness (Wu et al. 2011).

In the same year, Wu et al. (2011) developed a conceptual framework which can distinct the perceived benefits from the perceived risks. Using this model Wu et al. (2011) discovered that in the aspect of perceived benefits, companies seemed to be strategic-oriented rather than economic-oriented as the most popular benefits were "easy and fast to deploy to end-users" and "seems like the way of future".

Yang et al. (2015) used TOE framework to analyze SaaS adoption from the point of view of organizational users. This study suggests that for an organization to adopt the innovation, relevant users need to get ready in all three aspects: technological readiness which reflects how well employees are willing to use SaaS based on the perceived benefits of the technology, organizational readiness which demonstrates how ready potential users to adopt it in their daily work, and environmental readiness which shows how users are willing to adopt SaaS due to the perceived pressures from outside. Interesting finding of the study are:

— For SaaS adoption decision-making, users are more concerned about organizational and environmental readiness.

— For the intention to use SaaS in work, they are more concerned about technological characteristics of innovation.

Safari et al. (2015) applied TOE framework (combined with IDT) in order to rank factors affecting adoption of SaaS. In addition to IDT attributes, security and privacy of the technology were considered. Using this model, the author confirmed that all constructs of Technology (relative advantage, compatibility, complexity, trialability, observability and security and privacy), Organization (IT resource, sharing and collaboration culture) and environment (competitive pressure, social influence) significantly affect adoption of SaaS.

According to Martins et al. (2016), most previous studies related to SaaS adoption focused on the effects of the constructs on a single stage of SaaS adoption, and did not take into account other stages of innovation diffusion; therefore, they proposed a model based on TOE framework, DOI theory, and Institutional Theory for assessing the predictors of SaaS diffusion process. The results showed the direct influence of five constructs on the intention to adopt SaaS (relative advantage, complexity, technology competence, top management support, and normative pressures). Four constructs (technology competence, coercive pressures, normative pressures, and intention to adopt SaaS) had a direct effect on SaaS adoption, and three constructs (top management support, normative pressures, and SaaS adoption) had a direct influence on SaaS routinization.

Literature review of recent studies devoted to the factors affecting adoption of such emerging technologies as cloud computing, internet of things, and cognitive computing shows that all technology adoption models described in the previous section can be applied in context of emerging technologies. While a lot of studies related to adoption of cloud computing and sufficient amount of studies related to adoption of IoT and some cognitive computing technologies were found, no studies devoted to adoption of digital platforms which provide a bundle of emerging technologies were discovered.

1.4 Technology Adoption in Universities

Analysis of acceptance and use of technology in universities is important because it helps to predict students' attitude towards the new technologies. Adoption of new technologies can increase the educational and scientific results; therefore, a substantial research aimed at identification of factors affecting adoption of various technologies in educational context with help of different technology adoption models and frameworks was done.

For example, opportunities offered by cloud computing allow universities to have access to the advanced software, updated platform and high technology infrastructure without spending a lot of money at creating and maintaining large and costly IT infrastructure (Sabi 2016). Ercan (2010) says that by using cloud-computing students and university staff have the opportunity to quickly and economically access application platforms and resources. Yang (2013) also emphasizes that cloud computing helps students enter the job market because they will better understand the value of new technologies.

In order to identify factors affecting cloud computing in educational contexts Behrend, Wiebe, London, and Johnson (2011) applied a TAM3 model. The researchers found out that there was disagreement between the actual usage during studying and the intention to use a technology in the future which can be described by the fact that students make decisions about adoption of the technology based on their current needs, rather than the anticipated future need. Another interesting finding was that the ease-of-use perception was a much stronger predictor of adoption than the usefulness perception. This demonstrates that students may acknowledge the utility of a tool, but refuse to adopt it because it is not ease to use.

However, Martínez-Torres et al. (2008) in their research aimed to examine the technology acceptance model (TAM) of web-based e-learning tools used discovered that perceived ease of use did not have a significant influence on student's intention to use the technology, and it can be due to the fact that the students had sufficient knowledge or prior experience on computers in general, so they were not afraid to use a new computer-based tool.

In 2016, Huang (2016) developed a research model to explore the factors that influence students' continuance intention to use cloud services. The research was focused on influence of social and technological factors on students' continuance intention to use cloud services. The research findings suggest that social factors have significant influence on students' continuance intention; ease of use of cloud services is more important than usefulness for inexperienced users, while for experience users perceived usefulness is more important that perceived ease of use. The second finding can explain contradictory results received in researches of Martínez-Torres et al. (2008) and Behrend et al. (2011).

In order to analyze adoption of software engineering tools in academic context, Wrycza, Marcinkowski, and Gajda (2017) applied a modified UTAUT model where along with traditional UTAUT variables, additional variables such predictors as professional training and compatibility with other systems were tested. The results showed that behavioral intention was mainly explained by performance expectancy; influence of two new variable were also found significant. However, effort expectancy and social influence did not have a direct influence on behavioral intention to use software engineering tools.

Masrek and Samadi (2016) used a UTAUT model for identification of determinants of mobile learning adoption in higher education setting. The two additional variables, namely, perceived playfulness and self-management of learning, were added to traditional UTAUT predictors. Results of the study showed that all six variables were strong determinants of technology adoption.

Iqbal and Qureshi (2012) also tried to analyze acceptance of mobile learning in higher education with help of UTAUT model. The proposed research model included such factors as performance expectancy, effort expectancy, social influence, perceived playfulness, and self-management of learning which were hypothesized to be determinants of behavioral intention to use mobile learning. However, a similar study of Ng et al. (2015) revealed that only performance expectancy and self-management of learning affect a behavioral intention to adopt m-learning.

Analysis of scientific literature related to technology adoption in universities shows the existing body of knowledge takes into account primarily, such application areas as the improvement of the teaching process, the implementation of IT solutions in teaching, active learning, e-learning, mobile learning, or assessing the higher education environment. Besides that, the analysis shows that not all traditional predictors of technology adoption are consistently significant in university settings.

1.5 Research Gap and Research Questions

The analysis of scientific literature related to top emerging technologies and their adoption in different contexts reveals that such interconnected technologies as cognitive computing, Internet of Things, and cloud computing will have a significant influence on industry and academia in future. While the level of adoption of these technologies in Russia is low, the experts forecast two-digit growth rates during the next five years.

Although, there is a substantial research devoted to the factors affecting acceptance of these technologies separately, a little attention was paid to digital platforms providing access to these technologies in one place.

The adoption of such platforms in higher education allows universities using remote virtual machines, thus avoiding time-consuming and expensive installations as well as maintenance tasks. Besides that, by participating in educational programs offered by such platforms, universities can economically use advanced technologies based on very complex computing systems (Coccoli, Maresca, & Stanganelli 2016). For example, IBM Academic Initiative allows students to experiment with IBM Watson and other services available within the IBM Bluemix platform.

Adoption of digital computing platforms can increase the educational results which can be achieved through usage of modern technologies, group work, and better focus in computer science and software development courses (Coccoli et al. 2015). More importantly, by learning cognitive computing, Internet of Things, and cloud computing technologies provided by digital platforms, students are able to develop skills which will be in high demand for the next decade.

However, so far little attention has been paid to factors influencing adoption of digital computing platforms in universities, so there is a clear **research gap**.

The research problem of this thesis is adoption of emerging technologies in universities. Based on the research problem, the following research questions were formulated:

<u>Research question 1:</u> Which factors affect adoption of cognitive computing services among university students?

<u>Research question 2:</u> Which factors affect adoption of Internet of Things services among university students?

<u>Research question 3:</u> Which factors affect adoption of Platform-as-a-Service among university students?

<u>Research question 4:</u> Which factors affect adoption of advanced analytics by university students?

2. RESEARCH MODEL

This master thesis adopts a deductive research approach to explain causal relationships between variables; hence, the empirical research will start from formulation of research hypotheses based on the existing theoretical models, then the formulated hypotheses will be operationalized by defining model's constructs and measurements, after that, research design will be specified, survey conducted, and results analyzed using statistical methods.

This chapter explains the methodological framework of the study. First, research approach part describes research strategy and research type. Then, theoretical model part explains research variables, research hypothesis, and the research design choice. Finally, under the methodology section, the population, sample size, sampling method, and, data collection process are described.

2.1 Research Approach

There are three approaches to scientific research: quantitative, qualitative and mixed method. Qualitative approach is mainly used for exploring and understanding the attitude of people towards some phenomenon. Quantitative approach is used for testing models and theories by analyzing the relationship among variables. Mixed methods research combine qualitative and quantitative approaches for deeper understanding of the research area (Creswell 2013).

The choice of the specific approach for the research depends on type of data which is needed for answering research questions. Since the goal of this study is to analyze influence of pre-selected factors to technology adoption rather than identify all possible influential factors, quantitative research is more appropriate than qualitative one. Hence, for the purpose of this study, quantitative research was chosen, as it allows quantifying and prioritizing the contribution of each factor to technology adoption.

Another ontology of research types includes three types of research: exploratory, descriptive, and explanatory. Exploratory research is used when area of research is new, variable are unknown, so researcher needs to gain a deeper understanding of the problem. Descriptive studies are aiming to describe some phenomena or its characteristics, or discover relationships among some variables. Explanatory researches are used to explain relationships among variables or predict influence of some variables to others by testing causal hypotheses.

As it was demonstrated in the literature review, the topic of the study is not well covered, as there is a small number of research papers devoted to the factors influencing adoption of cognitive computing and advanced data analytics services, IoT services, and digital computing platforms where these technologies are integrated. Besides that, established technology adoption model will be used to analyze relationships between the factors. Finally, the aim of this study is to identify factors influencing adoption of emerging technologies in universities, that is establish causal relationships between variables; therefore, this research falls into the explanatory research category.

2.2 Theoretical Model

Based on the support of the UTAUT framework found in the literature, this model was selected as a basic theoretical model for the research. UTAUT has higher accuracy in explaining technology adoption success in comparison with alternative models. Alharbi (2014) claims that the model is more powerful and able to explain the variation in the acceptance of technology better than TAM and any other theoretical model (Alharbi, 2014).

Furthermore, Marques, Villate, and Carvalho (2011) have verified the adequacy of the UTAUT model in higher education context. UTAUT validation in this educational context has also been provided by Wong, Teo, and Russo (2013).

In addition, UTAUT model has been tested for adoption of some emerging technologies discussed in this thesis, for example, Al-Momani, Mahmoud, and Sharifuddin (2016) used UTAUT for modeling adoption of IoT services, Still the model has to be adjusted to fit the context of the present study. In the following, a conceptual model for adoption of emerging technologies in universities was developed.

2.2.1 Modified UTAUT

According to UTAUT, performance expectancy, effort expectancy, and social influence are theorized to influence behavioral intention to use a technology, while behavioral intention and facilitating conditions determine technology use. Also, such moderators as age, gender, voluntariness of use, and experience are theorized to moderate various UTAUT relationships.

In order to make the model fit the specific purpose of the research “Voluntariness of use” moderator is excluded because use of technologies in question is mandatory for all students. Moderator “age” is replaced with “academic degree” with three possible answers: “bachelor student”, “master student”, and “doctoral student”. “Experience” moderator was also replaced with “faculty” variable.

Finally, “Use Behavior” outcome was also excluded from the model because this study is not of longitudinal nature; therefore, it is impossible to know if student will actually use technologies in question in future. Since, according to UTAUT, facilitating conditions variable is theorized to have influence only on user behavior to use the technology, it was also omitted.

After the modifications, the model (see Figure 11) has three predictors (performance expectancy, effort expectancy, social influence), two moderators (gender, academic degree), and one dependent variable “behavioral intention”.

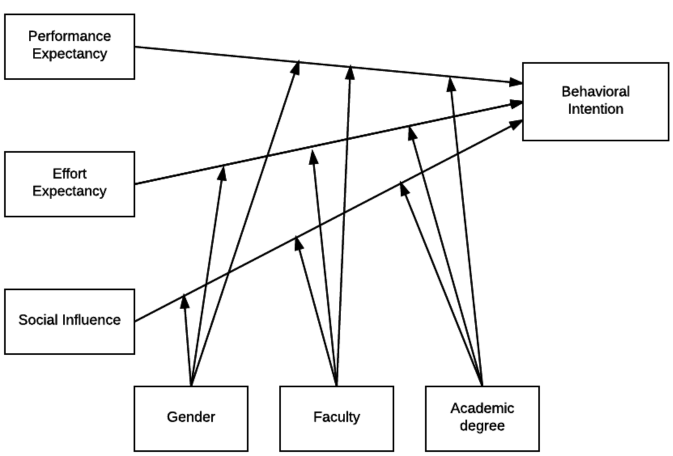

Figure 11: Modified UTAUT Model

According to the research questions which were formulated in the previous chapter, the modified UTAUT model will be applied for identification of factors which affect adoption of four emerging technologies included in digital computing platforms: cognitive computing, Internet of Things, advanced analytics, and Platform-as-a-Service. Therefore, multidimensional (multi-technological) implementation of the model will be used, where behavioral intention to use these technologies is hypothesized to influence behavioral intention to use a digital computing platform (see Figure 12).

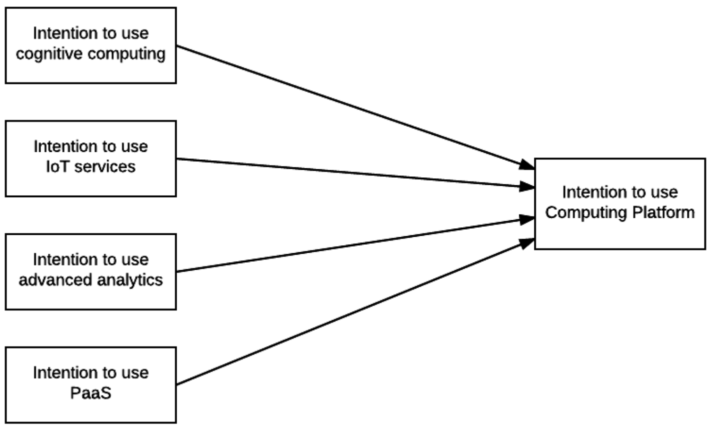

Figure 12: Factors Affecting Intention to Use a Computing Platform

2.2.2 Variables

To operationalize the research question into a set of research hypotheses for further analysis, it is necessary to describe the independent and dependent variables. For each of four technologies in question, there is one dependent and three independent variables.

The dependent variable in this research is student's intention to adopt a technology which is defined as "The person's subjective probability that he or she will perform the behavior in question" (Venkatesh et al. 2003).

Following are the definition of the three independent variables and corresponding items. Items to be measured were developed for each construct based on previous studies with modifications to fit the specific context of the research.

Performance expectancy is defined as the degree to which an individual believes that using the system will help him or her to attain gains in job performance. According to Venkatesh et al. (2003), performance expectancy is the strongest predictor of intention and remains significant at all points of measurement in both voluntary and mandatory settings.

Adapting performance expectancy to emerging technologies suggests that students will find these technologies useful because they enable them to accomplish learning tasks more quickly, effectively and flexibly which leads to better understanding of course materials and development of professional skills which can be used at future work place.

Taken the above together, this study hypothesizes:

Hypothesis 1: Performance expectancy has an influence on behavioral intention for adoption of cognitive computing technologies.

Hypothesis 2: Performance expectancy has an influence on behavioral intention for adoption advanced analytics services.

Hypothesis 3: Performance expectancy has an influence on behavioral intention for adoption of IoT services.

Hypothesis 4: Performance expectancy has an influence on behavioral intention for PaaS adoption.

Effort expectancy is defined as the degree of ease associated with the use of the system. This construct is proven significant in both voluntary and mandatory usage contexts, but only during the first time (Venkatesh et al. 2003).

In the context of emerging technologies, effort expectancy is about students' expectation of using emerging technologies without much effort and time needed to learn the technology. The simpler and quicker a student can understand the purpose of the technology and learn how to use it, the more is the intention to adopt it.

To this effect, this study hypothesizes that:

Hypothesis 5: Effort expectancy has an influence on behavioral intention for adoption of cognitive computing technologies.

Hypothesis 6: Effort expectancy has an influence on behavioral intention for adoption advanced analytics services.

Hypothesis 7: Effort expectancy has an influence on behavioral intention for adoption of IoT services.

Hypothesis 8: Effort expectancy has an influence on behavioral intention for PaaS adoption.

Social influence is defined as the degree to which an individual perceives that important others believe he or she should use the new system. When usage of the technology is mandatory, social influence is significant only at the beginning of individual's experience with the technology. In university context, social influence is about instructors' recommendations and peers attitude towards usage of the technology.

Grounded in UTAUT and justified by previous studies the following hypotheses are put forth:

Hypothesis 9: Social influence has an influence on behavioral intention for adoption of cognitive computing technologies.

Hypothesis 10: Social influence has an influence on behavioral intention for adoption advanced analytics services.

Hypothesis 11: Social influence has an influence on behavioral intention for adoption of IoT services.

Hypothesis 12: Social influence has an influence on behavioral intention for PaaS adoption.

In order to analyze influence of behavior intentions to use technologies in question separately to behavior intention to use IBM Bluemix platform, the following hypotheses were formulated:

Hypothesis 13: Behavioral intention to adopt cognitive computing technologies has an influence on behavioral intention for adoption of IBM Bluemix platform.

Hypothesis 14: Behavioral intention to adopt advanced analytics services has an influence on behavioral intention for adoption of IBM Bluemix platform.

Hypothesis 15: Behavioral intention to adopt internet of things services has an influence on behavioral intention for adoption of IBM Bluemix platform.

Hypothesis 16: Behavioral intention for PaaS adopt has an influence on behavioral intention for adoption of IBM Bluemix platform.

2.3 Research Design

The next crucial stage of scientific research is description of research design, which was defined by Cooper, Schindler, and Sun (2003), as "the strategy for a study and the plan by which the strategy is to be carried out. It specifies the methods and procedures for the collection, measurement, and analysis of data". The following section describes measurements, sampling, data collection and data analysis procedures.

2.3.1 Measurements

In order to analyze abstract constructs described in the previous section, item measures for all constructs should be developed.

Main criteria for evaluating a measurement tool are validity, reliability, and practicality. Validity is the extent to which a test measures what we actually want to measure, and three forms of validity can be specified: content validity, construct validity, and criterion-related validity. Reliability is concerned with estimates of the degree to which a measurement is free of random error, and its main dimensions are stability, equivalence, and internal consistency.

To ensure the validity and reliability of all measures, the measurement items for latent constructs within the proposed model were developed from prior studies related to adoption of ITC solutions in university settings. However, the items were slightly modified to make them relevant to context of the study and translated into Russian.

Each of the constructs included in the modified UTAUT model is supported by a set of two to three measures per technology. The detailed items for each construct and their sources are listed in Table 4.

For measuring constructs' items, a Likert scale was chosen as a rating scale. The Likert scale is the most popular type of rating scale which consists of statements, and respondents need to show agreement or disagreement with each statement. (Cooper et al. 2003). Since majority of studies related to the technology adoption used five-point scales, Likert scale (1-5), with anchors ranging from 'strongly disagree' to 'strongly agree', were used for all construct items in this study.

Table 4: Modified UTAUT model items

Variable	***Code***	***Item***	***Sources***
Performance expectancy	PE1X	I would find the system useful in my study.	(Venkatesh 2003)
	PE2X	Using the system increases the chances of getting a better job.	
Effort expectancy	EE1X	Practically every student may become proficient in using technology X.	(Venkatesh 2003)
	EE2X	It would be easy for me to become skillful at using the system.	
Social influence	SI1X	University instructors recommend using technology X.	(Venkatesh 2003)
	SI2X	People who are important to me think that I should use the system.	
Behavioral intention	BI1X	I predict I would use technology X on the future job.	(Venkatesh 2003)
	BI2X	I plan to use the technology X in the next year.	

2.3.2 Sampling Design

Sampling design includes identification of target population, definition of sample, and selection of sampling method and minimum sample size.

The target population of the study includes full-time bachelor, masters, and doctoral students who study at IT-related faculties of Russian universities. However, it is not feasible to conduct the survey among all people from the target population because of time, financial, and other restrictions; therefore, it is necessary to select some elements of the population, analysis of which allows to make generalizable conclusions.

A sample is considered good if it represents the characteristics of the target population, but there is an agreement among researchers that no sample can ideally represent its population. The sample can be considered valid if it has little systematic variance and random sampling error is within acceptable limits for the study's purpose (Cooper et al. 2003).

There are a lot of sampling methods which differ in their representation basis (restricted, unrestricted) and element selection techniques (probability, nonprobability). For the purpose of the study, a convenience sampling method was selected because of its simplicity and cheapness.

The sample size plays an influential role in the reliability test during structural equation model (SEM) analysis. While researchers agree that using SEM larger sample sizes result in increased sensitivity to detect differences among the data (Khine 2003), there is no commonly accepted method for determining minimum required sample size. According to Quintana and Maxwell (1999), the main considerations for determining sample size are number of observations per parameter, the number of observations required for fit indexes, and the number of observations per degree of freedom.

When using a Maximum Likelihood (ML) estimation approach, Jackson (2003) suggested that ideal ration of sample size to the number of model parameters is 20:1, though ratio of 10:1 is also appropriate to get trustworthy results.

A recommended sample size in absolute terms was suggested by Tanaka (1987) and Hadow (1985) who said that sample size of 400 or 500 is needed. Anderson and Gerbing (1984) found that a sample size of 150 would usually be big enough to obtain a converged solution. Ding, Velicer, and Harlow (1995) recommended a minimum sample size of between 100 to 150 participants. Bollen (1989) recommended a minimum sample size of at least 100. With sample size less than 100, almost any type of SEM may be incorrect unless a very simple model is evaluated (Kline 2015).

Considering the above-mentioned recommendations and the fact that “typical” number of respondents in studies where SEM is used is about 200 (Kline 2015), the target sample size for the study was set to 200.

Considering that, not all invited respondents would actually participate in the survey, 450 invitations were sent to the targeted students which were selected using the simple random sampling technique. To maximize the response rate, potential respondents were incentivized by small digital gifts.

2.3.3 Data Collection Design

Considering the research questions formulated in the previous chapter and limitation of resources, the research strategy selected for this research is a survey. Survey is the most popular strategy for exploratory and descriptive research in business and management area (Saunders 2013).

Self-administered questionnaires distributed in social networks among potential respondents were chosen as the instrument for data collection because it allows retrieving large amount of data from students in fast and economical manner.

Google Forms software was selected as a tool in order to make the survey available for online audience.

The survey was distributed among bachelor, masters, and PhD students from Faculty of Mathematics and Mechanics and Faculty of Applied Mathematics and Control Processes of Saint Petersburg State University. Interested students from other faculties of Saint Petersburg State University were not restricted from participated in the survey.

To mitigate the risk of low response rate invitation messages and reminders to potential responders were sent in social networks to encourage the survey participation. Besides that, the respondents were notified that their responses to the survey questions are confidential and will be used only for the purpose of the research.

The questionnaire consisted of administrative, target, and classification questions. Classification questions covered such sociological-demographic variables as gender, academic degree, and faculty. Target questions were divided into four sections where each section was devoted to one of four technologies in question.

To familiarize respondents with technologies, each section included a brief description of the technology, a list of sub-technologies, examples of applications, and jobs where the technology could be applied. Besides that, each section contained eight closed obligatory questions related to the model’s constructs, and one open mandatory question about respondent’s previous experience with the technology.

Data was collected during April 2017. Throughout the period of data collection, 150 questionnaires out of 450 were returned (yielding a participation rate of 33%) and analyzed using data analysis software - IBM SPSS AMOS 24.0 and IBM Watson Analytics.

2.3.4 Data Analysis Procedures

The statistic method selected for testing the research model based on collected data is Structural equation modeling (SEM).

SEM is a type of statistic method used to examine the accuracy of constructive relationship, explore relationship between the observable observed and latent variables, as well as defining the interactive relationship between each other. When properly employed, it offers great potential for theory development and construct validation.

Due to the nature of social and behavioral sciences, which are typically constructed by some unobservable variance, structural SEM became a quasi-standard in marketing and management research devoted to analysis of the cause-effect relations.

There are multiple approaches for structural equation modeling. Full-information (for example, Maximum Likelihood or Generalized Least Squares) estimation approach in connection with the common factor model have relative strengths for theory testing and development, while Partial Least Squares estimation approach is more appropriate for prediction. Since the objective of the research is to test a theoretical model, a full-information estimation approach will be used for structural equation modeling.

Nowadays, most structural equation models described in the literature are analyzed using Maximum Likelihood (ML) method. Besides that, this method is the default in majority of SEM computer programs. According to Kline (2015), ML estimates in big samples are asymptotically unbiased, efficient, and consistent, when all statistical requirements (independence of observations, multivariate normality, and independence of the exogenous variables and residuals) are met and the theoretical model is specified correctly. The fit function in ML estimation relates to the discrepancy between sample covariance and one predicted by the model.

Normally, a structural equation model consists of two parts: measurement model representing a set of observable variables as multiple indicators of a smaller set of latent variables, and path model representing dependencies between the latent variables (McDonald & Ho 2002).

This study follows the two-step approach recommended by Anderson and Gerbing (1988). This approach emphasizes the analysis of the measurement and structural models as two conceptually distinct models. Jöreskog and Sörbom (2003) argue that if the observable variables for a construct do not measure that construct, then it does not make sense to test the structural model. Therefore, first, the measurement model should be assessed to examine reliability and validity and, second, the structural model can be assessed to test the research hypotheses and the suitability of the model.

Hence, the first step is to analyze the measurement model which represents the hypothesis about relationship between the latent variables and corresponding observed variables. The objective of this step is to determine the extent to which items designed to measure a particular latent construct actually do so.

A measurement model can be evaluated using confirmatory factor analysis (CFA) where both the number of factors and their correspondence with the indicators are explicitly specified. In this case, the latent constructs are considered common factors and the error or specific terms are uncorrelated. A generic measurement model for one technology is shown in Figure 13.

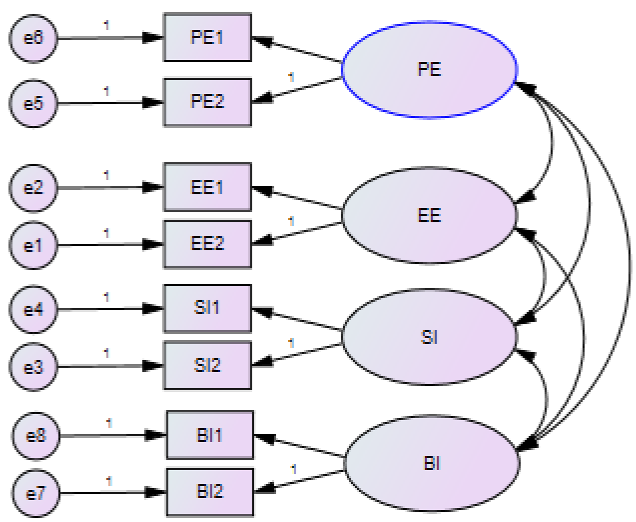

Figure 13: Generic Measurement Model

The second step is to create the structural model that would demonstrate the path coefficients, showing nature and magnitude of the relationships between the latent variables identified during the previous step. A generic structural model for one technology is shown in Figure 14.

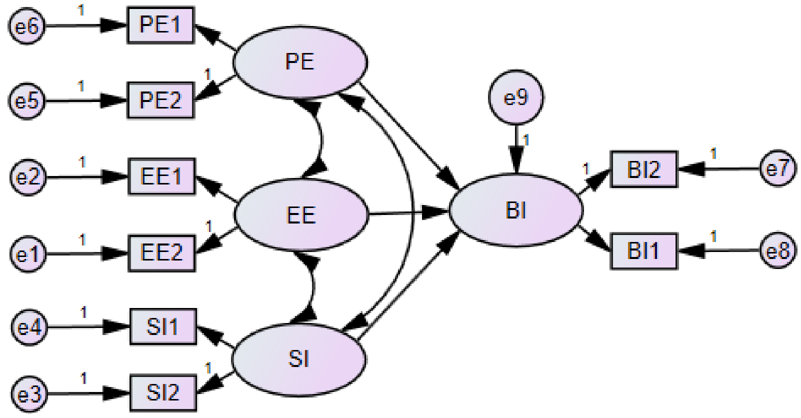

Figure 14: Generic Structural Model

When the measurement and structural models are combined, the result is a complex statistical model which can be used to evaluate relationships between variables (Hoyle 1995).

Besides that, the survey results were also analyzed using IBM Watson Analytics platform which is able to determine predictors of a selected dependent variable. Unlike structural equation modeling approach, analysis in modern analytics platforms does not require a predefined structural model; therefore, it can help to discover unexpected relationship between model items. Furthermore, the study of Faizullov and Yablonsky (2017) has shown that suggestions of IBM Watson Analytics can be used to create effective predictive models.

2.4 Chapter Summary

In order to answer to the research questions formulated in the first chapter, survey research strategy was selected. Survey questions were based on the multidimensional implementation of modified UTAUT model which describes influence of performance expectancy, effort expectancy, and social influence on technology adoption intentions. To test the formulated hypothesis, results of the questionnaire will be analyzed using structural equation modelling approach and IBM Watson Analytics platforms.

3. RESULTS

The research model shown in Figure 11 was analyzed using SEM, supported by IBM SPSS AMOS 24.0. SPSS AMOS allows testing research hypothesis by confirming relationships between observed and latent unobserved variables.

The statistical analyses carried out were Descriptive Analysis, Confirmatory Factor Analysis for assessing convergent validity and discriminant validity, and Structural Equation Modelling for testing the formulated research hypotheses.

In addition to SEM, survey results were also analyzed using IBM Watson Analytics in order to gain additional insights about factors affecting adoption of emerging technologies among university students. Watson predictive analytics uses ad-hoc statistical analysis, predictive modeling, data mining to discover patterns and trends in structured and unstructured data.

3.1 Sample Profile

Table 5, presented below, provides the demographic profile of the respondents. The profile includes gender, academic degree, and faculty.

Table 5: Characteristics of Respondents

Characteristic	***Number***	***Percentage***
Gender		
Female	70	47.3
Male	80	52.7
Faculty		
Mathematics and Mechanics	77	50.7
Applied Mathematics and Control Processes	70	47.3
Faculty of arts	1	0.6
Graduate School of Management	2	1.4
Academic degree		
Bachelor student	111	73.8
Master student	29	19.5
PhD student	8	5.4
Instructor	2	1.3

Out of 150 respondents, 52.7% were males while the remaining 47.3% were females. In terms of faculty, the majority indicated to study at the faculty of Mathematics and Mechanics (50.7%) and faculty of Applied Mathematics and Control Processes (47.3%). Regarding academic degree, 71.6% of respondents were bachelor students, 19.6% were master students, and 5.4% were doctoral students.

As the Figure 15 shows, among the respondents, 13.3% had prior experience with cognitive computing technologies (computer vision, natural language processing, neural networks, deep learning, chatbots), 48% were familiar with advanced analytics tools, 31.3% used some Internet of Things services, and only 13.3% used platforms-as-a-service (Microsoft Azure, Heroku, AWS, IBM Bluemix) for development of software applications. More than half of students, who reported a prior experience with PaaS, mentioned that it was a Microsoft Azure platform.

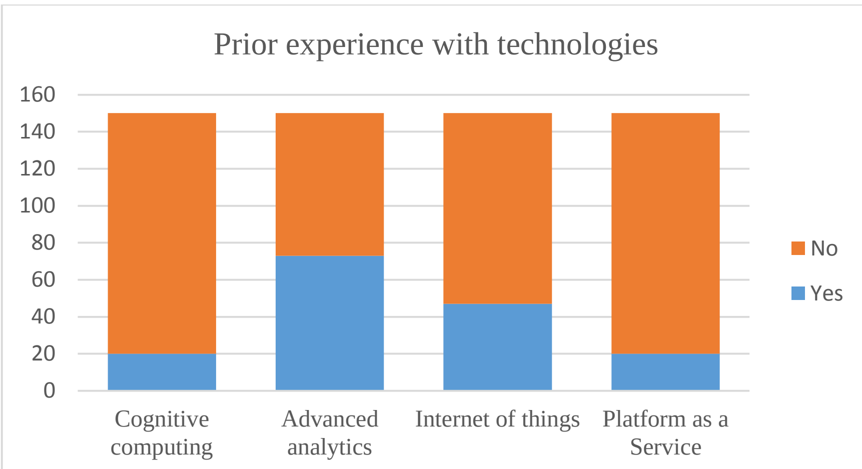

Figure 15: Prior Experience of Respondents with Analyzed Technologies

3.2 Measurement Model

The measurement model describes how well measured variables represent a construct that cannot be measured directly (Hair et al. 2006). It provides a confirmatory assessment of convergent validity and discriminant validity (Campbell & Fiske, 1959).

Before conducting path analysis for the research model and testing significance of relationships in the structural model, it is important to assess measurement items in the questionnaire for construct reliability and validity.

A confirmatory factor analysis using SMSS AMOS was applied to evaluate adequacy of the measurement models on the criteria of model fit, reliability, convergent validity, and discriminant validity.

3.2.1 Normality

Maxim Likelihood estimation approach, which is used in this study, requires the assumption of multivariate and univariate normality; otherwise, it can result in biased standard errors and incorrect test statistics (McDonald & Ho 2002).

To test for univariate normality the skewness and kurtosis of each observed variable was assessed by skew index and kurtosis index. As shown in Appendix 1, the skewness and kurtosis requirements fulfilled the benchmark values which are 3 and 10, respectively.

Multivariate normality can be assumed when the Mardia's coefficient is less than p * (p+2), where p is the number of observed variables. As each measurement model has 8 observed variables, the Mardia's coefficient for each model's factor should be less than 80.

Table 6: Mardia's Coefficients for the Models' Factors

Statistic	***Cognitive computing***	***Advanced analytics***	***Internet of Things***	***PaaS***
Mardia's coefficient	2.7	24.3	14.4	14.3

As Table 6 shows, the Mardia's coefficients are less than 80, so requirement for multivariate normality is fulfilled.

3.2.2 Reliability

To confirm the reliability of the measurement items, a composite reliability was estimated. The composite reliability is similar to Cronbach's alpha, except that it also takes into account the factor loadings rather than assuming that each measure is equally weighted in the composite load determination.

Table 7: Composite Reliability for the Models' Factors

Factor	***Cognitive computing***	***Advanced analytics***	***Internet of Things***	***PaaS***
Performance expectancy	0.705	0.689	0.608	0.676
Effort expectancy	0.663	0.602	0.692	0.701
Social influence	0.634	0.682	0.719	0.690
Behavioral intention	0.782	0.689	0.753	0.854

As shown in Table 7, most of the composite reliability values exceeded or were close to the commonly acceptable level of 0.7 (Nunnally, 1978). The composite reliability which is much smaller than the thresholds value was found for SI in measurement model for cognitive computing, EE in model for advanced analytics, and PE in model for IoT.

3.2.3 Convergent Validity

Convergent validity is verified when inter-correlations of items which theoretically measure the same construct are at least moderate in magnitude.

Convergent validity was evaluated for measurement scales using two criteria suggested by Fornell and Larcker (1981): all indicator factor loadings should be significant and exceed 0.50 (Hair et al. 1992) and average variance extracted (AVE) for each construct should be greater than 0.5.

Table 8: Factor Loading

Factor	***Cognitive computing***	***Advanced analytics***	***Internet of Things***	***PaaS***
Performance expectancy				
PE1	0.724	0.689	0.699	0.793
PE2	0.751	0.678	0.622	0.631
Effort expectancy				
EE1	0.769	0.646	0.771	0.840
EE2	0.636	0.667	0.682	0.623
Social influence				
SI1	0.543	0.692	0.725	0.695
SI2	0.808	0.746	0.773	0.756
Behavioral intention				
BI1	0.764	0.776	0.772	0.831
BI2	0.837	0.672	0.782	0.894

Examination of the measurement model revealed that all item loadings, except for SI1 in model for cognitive computing, exceeded the threshold value of 0.5. Therefore, it can be considered that all items have acceptable convergence on the intended constructs.

Moreover, the average variances extracted for most of items was around the threshold value (see Table 9), which means that more than one-half of the variance observed in the items was attributed to the models' construct.

Table 9: Average Values Extracted for the Models' Factors

Factor	*Cognitive computing*	*Advanced analytics*	*Internet of Things*	*PaaS*
Performance expectancy	0,544	0,467	0,438	0,514
Effort expectancy	0,498	0,431	0,530	0,547
Social influence	0,474	0,518	0,562	0,527
Behavioral intention	0,642	0,527	0,604	0,745

Since both criteria of convergent validity for most of the measurement model items exceed the respective threshold values, it confirms that the scale has sufficient convergent validity.

3.2.4 Discriminant validity

The study also assessed discriminant validity of the model's constructs. Discriminant validity is established when items theoretically belonging to different constructs are not related, that is intercorrelations of items which theoretically measure the different constructs are not too high.

The discriminant validity of the constructs was assessed using the approach suggested by Fornell and Larcker (1981). The square root of the AVE for each construct should be greater than the correlations between two composite constructs.

Table 10: Discriminant Validity of Measurement Model for Cognitive Computing

Factor	*AVE*	*1*	*2*	*3*	*4*
1. Performance expectancy	0,544	1	0.070	0.284	0.389
2. Effort expectancy	0,498	0.070	1	0.147	0.239
3. Social influence	0,474	0.284	0.147	1	0.406
4.Behavioral intention	0,642	0.389	0.239	0.406	1

AVE, average variance extracted; Off-diagonal elements are the correlation coefficients.

As indicated in Table 10, the AVE for each factors of measurement model for cognitive computing is higher than the correlations between two composite constructs, so the test of discriminant validity was acceptable and sufficient discriminant validity was confirmed.

Table 11: Discriminant Validity of Measurement Model for Advanced Analytics

Factor	***AVE***	***1***	***2***	***3***	***4***
1. Performance expectancy	0,467	1	0.241	0.455	0.426
2. Effort expectancy	0,431	0.241	1	0.207	0.246
3. Social influence	0,518	0.455	0.207	1	0.530
4.Behavioral intention	0,527	0.423	0.246	0.530	1

AVE, average variance extracted; Off-diagonal elements are the correlation coefficients variance.

As indicated in Table 11, the AVE for each factors of measurement model for advanced analytics is higher or close to the correlations between two composite constructs, so the test of discriminant validity was acceptable and sufficient discriminant validity was confirmed.

Table 12: Discriminant Validity of Measurement Model for Internet of Things

Factor	***AVE***	***1***	***2***	***3***	***4***
1. Performance expectancy	0,438	1	0.310	0.418	0.528
2. Effort expectancy	0,530	0.310	1	0.278	0.510
3. Social influence	0,562	0.418	0.278	1	0.512
4. Behavioral intention	0,604	0.528	0.510	0.512	1

AVE, average variance extracted; Off-diagonal elements are the correlation coefficients variance.

As indicated in Table 12, the AVE for the three factors of measurement model for internet of things is higher than the correlations between two composite constructs. However, the AVE for performance expectancy is much lower than the correlation between performance expectancy and behavior intention.

Table 13: Discriminant Validity of Measurement Model for PaaS

Factor	***AVE***	***1***	***2***	***3***	***4***
1. Performance expectancy	0,514	1	0.176	0.459	0.488
2. Effort expectancy	0,547	0.176	1	0.229	0.467
3. Social influence	0,527	0.459	0.299	1	0.563
4.Behavioral intention	0,745	0.488	0.467	0.563	1

As indicated in Table 13, the AVE for each factors of measurement model for PaaS is higher or close to the correlations between two composite constructs, so the test of discriminant validity was acceptable and sufficient discriminant validity was confirmed.

3.2.5 Model Fit

After estimating measurement models, given a converged and proper solution, it is necessary assess how well the models account for the data with one or more overall goodness-of-fit indices. Therefore, confirmatory factor analysis (CFA) was applied to test the adequacy of the measurement model.

For a good model fit, Bentler (1990) suggested that the Chi-square value, normalized by degrees of freedom (χ^2/df), should not exceed 3, the goodness of fit index (GFI) should exceed 0.9, adjusted goodness-of-fit index (AGFA) should be greater than 0.8, the normalized fix index (NFI) and comparative fit index (CFI) should exceed 0.9.

Table 14 presents five popular model-fit measures which were used to assess the model's overall goodness of fit.

Table 14: Fit Indices for Measurement Models

Goodness-of-fit measure	***Recommended value***	***Cognitive computing***	***Advanced analytics***	***Internet of Things***	***PaaS***
$\boldsymbol{\chi^2/df}$	≤ 3.00	2.976	2.941	2.912	1.924
$\boldsymbol{GFI}$	≥ 0.9	0.930	0.925	0.929	0.955
$\boldsymbol{AGFI}$	≥ 0.8	0.819	0.808	0.818	0.884
$\boldsymbol{NFI}$	≥ 0.9	0.893	0.901	0.905	0.945
$\boldsymbol{CFI}$	≥ 0.9	0.923	0.928	0.931	0.972

Since almost all fit indices for the measurement models in this study were all within satisfactory ranges, the measurement model analysis has shown a good fit according to the goodness-of-fit indices.

In summary, all measurement models demonstrated adequate reliability, convergent validity, and discriminant validity.

3.3 Structural Models

Structural model can be described as a part of the model that specifies how the latent variables relate to each other. Assessment of the structural model is required for testing of theoretical hypothesis formulated in the second chapter.

Fit criteria of structural models are assessed in terms of absolute, incremental, parsimony fit measures. The structural models were tested with a similar set of model-fit indices as measurement models. Analysis shows a good fit according to the estimates of different goodness-of-fit indices listed in the Table 15 which provides the threshold value and the actual values for individual indices.

Table 15: Fit Indices for Structural Models

Goodness-of-fit measure	***Recommended value***	***Cognitive computing***	***Advanced analytics***	***Internet of Things***	***PaaS***
χ^2/df	≤ 3.00	2.726	2.901	3.003	2.906
GFI	≥ 0.9	0.964	0.930	0.960	0.974
$AGFI$	≥ 0.8	0.873	0.819	0.862	0.872
NFI	≥ 0.9	0.935	0.901	0.940	0.952
CFI	≥ 0.9	0.956	0.928	0.958	0.967

3.4.1 Structural Model for Cognitive Computing

Table 16 presents the path coefficients and their significance for each hypothesis related to the adoption of cognitive computing services. Overall, two paths in the model turned out to be significant with p-value less than 0.05.

Table 16: Hypothesis Testing for Cognitive Computing

Hypothesis	*Related path coefficient*	*Significance*	*Result*
H1	0.759	< 0.001	Accepted
H5	0.406	< 0.001	Accepted
H9	-	> 0.05	Rejected

The analytical results show that performance expectancy (β=0.759, p<0.01) and social influence (β=0.406, p<0.001) positively affect behavioral intention to use cognitive computing services with performance expectancy having the biggest influence, so hypotheses 1 and 5 were accepted. However, no statistical evidence regarding the impact of social influence and on behavioral intention was found, this means that hypothesis 9 was rejected.

Structural model for adoption of cognitive computing services is shown in Figure 16.

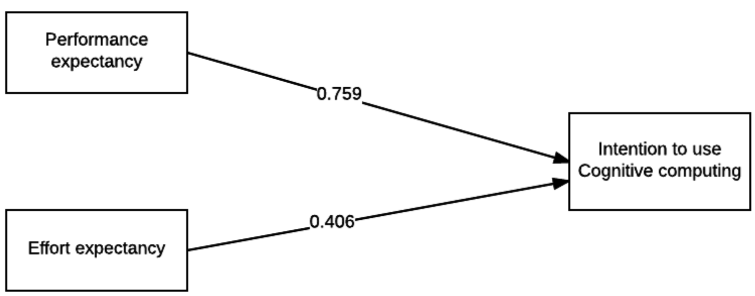

Figure 16: Structural Model for Adoption of Cognitive Computing Services

Multiple-group analysis of the structural model for the adoption of cognitive computing services using Chi-square difference test in IBM SPSS Amos shows that gender moderates ($p < 0.05$) the influence of effort expectancy on behavioral intention: effort expectancy has higher path weight for females (0.56) than for males (0.32). Besides that, academic degree does not moderate influence of performance expectancy and effort expectancy on students' behavioral intentions to use cognitive computing services.

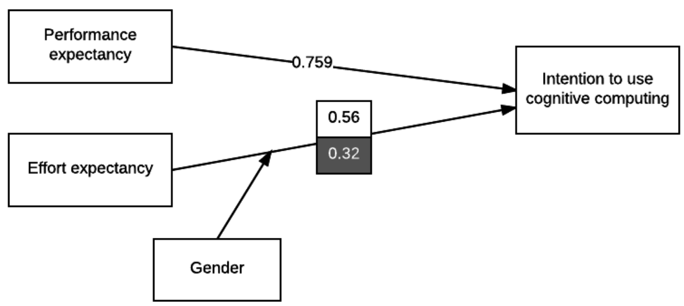

Figure 17: Structural Model with Moderators for Adoption of Cognitive Computing Services

3.4.2 Structural Model for Advanced Analytics

Table 17 presents the path coefficients and their significance for each hypothesis related to the adoption of advanced analytic services. Overall, only two paths in the model turned out to be significant with p-value less than 0.05.

Table 17: Hypothesis Testing for Advanced Analytics

Hypothesis	***Related path coefficient***	***Significance***	***Result***
H2	0.211	0.05	Accepted
H6	-	> 0.05	Rejected
H10	0.857	0.001	Accepted

There was no significant relationship found between effort expectancy and behavior intention to use advanced analytics services, so the hypotheses 6 was rejected. However, analysis shows that performance expectancy and social influence were significant path predictors of behavior intention to use advanced analytics services, thus the hypotheses H2 and H10 were supported. Structural model for adoption of advanced analytics services is depicted in figure 18.

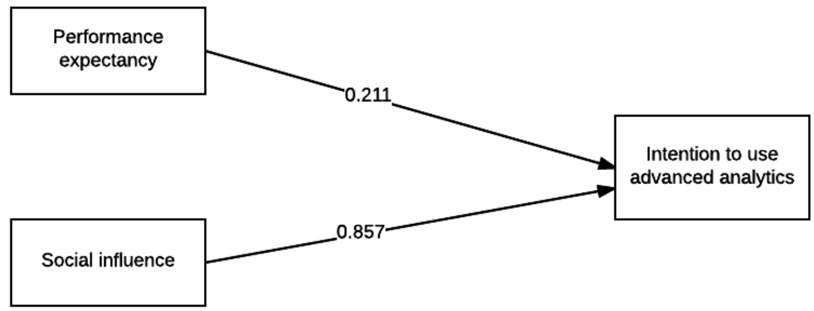

Figure 18: Structural Model for Adoption of Advanced Analytics Services

Multiple-group analysis of the structural model for the adoption of advanced analytics tools shows that gender does not moderate the influence of performance expectancy and social influence on behavioral intention. Moreover, academic degree also does not moderate influence of performance expectancy and social influence on students' behavioral intentions to use advanced analytics services.

3.4.3 Structural Model for Internet of Things Services

Table 18 presents the path coefficients and their significance for each hypothesis related to the adoption of Internet of Things services. Overall, two paths in the model turned out to be significant with p-value less than 0.05.

Table 18: Hypothesis Testing for Internet of Things

Hypothesis	***Related path coefficient***	***Significance***	***Result***
H3	-	> 0.05	Rejected
H7	0.616	0.001	Accepted
H11	0.445	0.001	Accepted

The analytical results show that effort expectancy (β=0.616, p=0.001) and social influence (β=0.445, p=0.001) positively affect behavioral intent to use a platform for the Internet of Things. These results provide support for hypotheses H7 and H11. Performance expectancy had no significant impact on intention to use Internet of Things services resulting in rejection of H3.

Visual representation of the structural model for adoption of IoT services is shown in Figure 19.

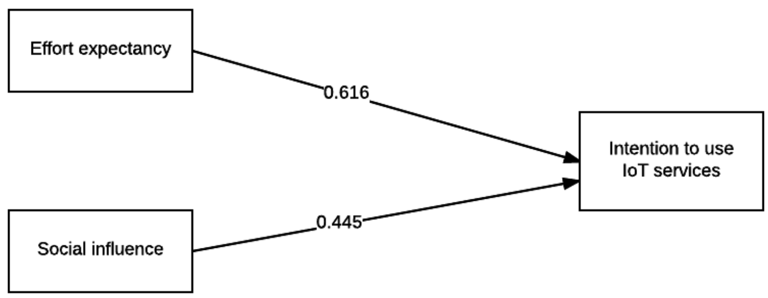

Figure 19: Structural Model for Adoption of IoT Services

Multiple-group analysis of the structural model for the adoption of IoT services that gender moderates ($p < 0.05$) the influence of effort expectancy on behavioral intention: effort expectancy has higher path weight for females (0.67) than for males (0.40). Furthermore, academic degree does not moderate influence of social influence and effort expectancy on students' behavioral intentions to use IoT services.

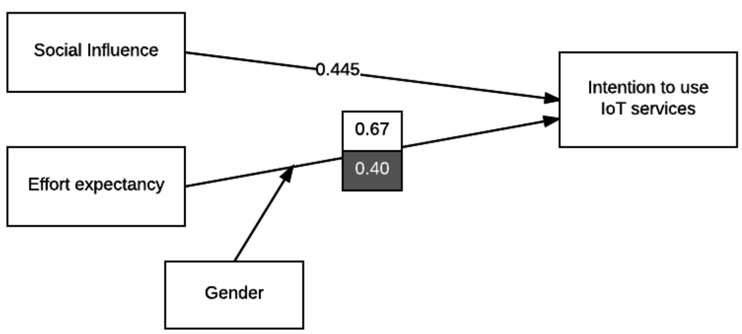

Figure 20: Structural Model with Moderators for Adoption of IoT Services

3.4.4 Structural Model for PaaS

Table 19 presents the path coefficients and their significance for each hypothesis related to the adoption of PaaS. Overall, two paths in the model turned out to be significant with p-value less than 0.05.

Table 19: Hypothesis Testing for PaaS

Hypothesis	***Related path coefficient***	***Significance***	***Result***
H4	0.793	0.001	Accepted
H8	0.351	0.003	Accepted
H12	-	> 0.05	Rejected

The analytical results show that performance expectancy (β=0.793, p<0.001) and effort expectancy (β=0.351, p=0.003) have significant influence on behavioral intention to use Platform-as-a-Service, thus supporting hypothesis 4 and hypothesis 8.

However, no proof of a link between social influence and behavioral intention was discovered, so hypothesis 12 was rejected.

Figure 21 demonstrates the structural model for adoption of platform-as-a-service.

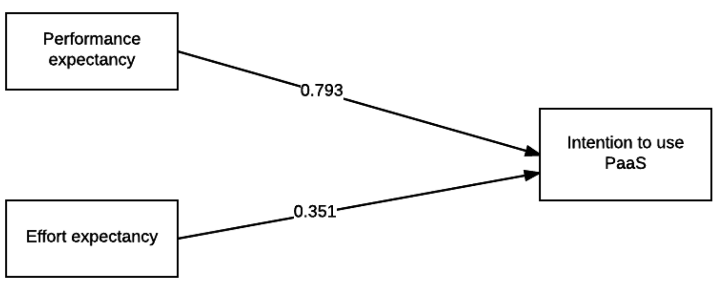

Figure 21: Structural Model for Adoption of PaaS

Multiple-group analysis of the structural model for the adoption of Platform-as-a-Service shows that gender moderates ($p < 0.05$) the influence of effort expectancy on behavioral intention: effort expectancy has higher path weight for females (0.44) than for males (0.30). Besides that, academic degree does not moderate influence of performance expectancy and effort expectancy on students' behavioral intentions to use PaaS.

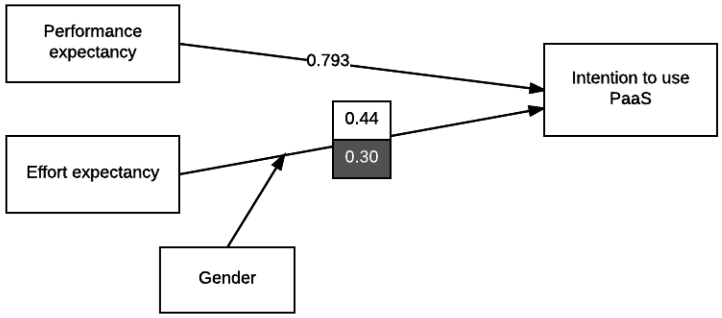

Figure 22: Structural Model with Moderators for Adoption of PaaS

3.4.5 Structural Model for IBM Bluemix Platform

Table 20 presents the path coefficients and their significance for each hypothesis related to adoption of IBM Bluemix platform. Overall, two paths in the model turned out to be significant with p-value less than 0.05.

Table 20: Hypothesis Testing for IBM Bluemix

Hypothesis	***Related path coefficient***	***Significance***	***Result***
H13	0.224	0.02	Accepted
H14	-	> 0.05	Rejected
H15	-	> 0.05	Rejected
H16	0.320	0.001	Accepted

Results of the analysis show behavioral intention to use PaaS is the strongest predictor of behavior intention to use IBM Bluemix platform (β=0.320, p=0.001). Another significant predictor of behavior intention to use IBM Bluemix platform is behavioral intention to use cognitive computing services (β=0.3224, p<0.05). Hence, hypotheses 13 and 16 are accepted, but no statistical evidence was found in support for hypotheses 14 and 15, that is behavior intentions to use advanced analytics services and internet of things services do not have significant influence on intention to use IBM Bluemix.

Structural model for adoption of IBM Bluemix platform is shown in Figure 23.

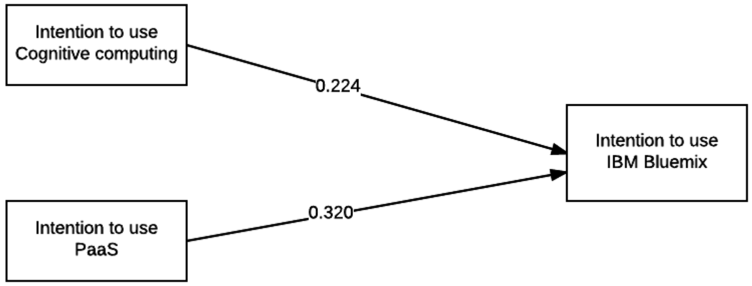

Figure 23: Structural Model for Adoption of IBM Bluemix Platform

3.4 Predictive Analysis with Watson Analytics

In Watson predictive analytics, strength of the relationships between variables is evaluated by predictive strength which measures the importance of a field in relationship to its ability to help predict the outcome. The statistical model which is used in Watson Analytics to calculate a predictive strength is chi-squared automatic interaction detection (CHAID) decision tree.

Predictive strengths of relationships between different factors and behavior intentions to adopt technologies are represented in the Table 21 below.

Table 21: Predictive Strength of Drivers of Technology Adoption (in percent)

Factor	*Cognitive computing*		*Advanced analytics*		*Internet of Things*		*PaaS*	
	BI1	*BI2*	*BI1*	*BI2*	*BI1*	*BI2*	*BI1*	*BI2*
Performance expectancy								
PE1	-	11	19	19	21	24	40	31
PE2	22	38	25	24	-	-	22	26
Effort expectancy								
EE1	12	-	18	-	30	18	28	20
EE2	12	-	-	-	24	-	-	-
Social influence								
SI1	-	12	12	18	19	22	22	27
SI2	25	30	25	33	15	27	18	29

3.4.1 Adoption of Cognitive Computing Services

Results of the analysis show that the strongest predictor (predictive strength - 25%) of students' intentions to use cognitive computing services in near future (BI1) is a social influence by university instructors (SI2), while the second strongest predictor with slightly lower predictive strength (22%) is increased chance to get a better job after graduation (PE2). Effort expectancy (EE2 and EE2), social influence by peers (PE1), and better understanding of course materials (PE1) have low influence on behavioral intention to use cognitive computing technologies by students.

Students' intentions to use the cognitive computing services after graduation (BI2) are influenced by increased chance to get a better job after graduation (PE2, 38%) and social influence by university instructors (SI2, 30%). Social influence by peers (PE1, 11%), and better understanding of course materials (SE1, 12%) have lower predictive power, while no relationships between effort expectancy and intention to use cognitive computing services after graduation were found.

Besides that, analysis with Watson predictive analytics shows that perceived benefit of using cognitive computing (PE1 and PE2) is correlated with social influence by university instructors (SI2); while perceived effortless (EE1 and EE2) is correlated with social influence by peers (SI2), though the strength of this relationship is rather small (predictive strength - 22%).

Table 22: Analysis of averages across groups for cognitive computing adoption

Factor	***Performance expectancy***		***Effort expectancy***		***Social influence***		***Behavior intention***	
	PE1	*PE2*	*EE1*	*EE2*	*SI1*	*SI2*	*BI1*	*BI2*
Gender								
Male	3.2	3.9	4.0	3.3	2.6	2.5	3.7	3.3
Female	3.3	3.9	4.1	3.9*	2.5	2.5	3.6	3.2
Degree								
Bachelor	3.3	4.0	4.0	3.6	2.7	2.6	3.7	3.3
Masters	3.1	3.7	4.0	3.7	2.4	2.4	3.4	2.8
PhD	3.5	3.3	4.3	3.5	2.4	2.0	3.0	3.9
Faculty								
Math-Mechanic	3.2	3.9	4.0	3.7	2.6	2.5	3.5	3.2
Applied Mathematics	3.3	3.9	4.1	3.6	2.6	2.5	3.7	3.2

* p-value < 0.05

Table 22 shows average values of model's items related to adoption of cognitive computing services across different groups of respondents. Analysis of means using independent T-tests and one-way ANOVA shows that the only significant difference was found between average effort expectancy (EE2) for males and females.

3.4.2 Adoption of Advanced Analytic Services

Strong relationships were found between students' intention to use advanced analytical services in near future and increased chances to get a better job (PE2, 25%), and social influence by and university instructors (SI2, 25%). Weaker relationships were discovered between students' behavioral intentions and effort expectancy (EE1, 18%) and better understanding of course materials (PE1, 20%). No significant influence was found in support of relationship between social influence by peers (SI1) and behavioral intention to use advanced analytical tools.

Students' intentions to use the advanced analytic services after graduation (BI2) are primarily affected by instructors' social influence (SI2, 33%) and increased chances to get a better job (PE2, 24%). Social influence by peers (SI1) and better understanding of course materials (PE1) have smaller predictive power (18% and 19% respectively), while no relationships between effort expectancy and intention to use advanced analytics tools after graduation were found.

Besides that, results of the analysis show that perceived benefit of using advanced analytical tools for educational purposes (PE1) is affected by social influence by instructors (SI2).

Table 23 demonstrates average values of model's items related to adoption of advanced analytics services across different groups of respondents.

Analysis of means using independent T-tests and one-way ANOVA shows that females have greater average perceptions about utility of advanced analytics for educational purposes. Besides that, females have greater effort expectancy than males; it means that they believe more strongly than males that they can become proficient at using advanced analytic tools. Furthermore, PhD students reported lower average intentions to use advanced analytics in future than BA and MS students did.

Table 23: Analysis of Averages across Groups for Advanced Analytics Adoption

Factor	*Performance expectancy*		*Effort expectancy*		*Social influence*		*Behavior intention*	
	PE1	*PE2*	*EE1*	*EE2*	*SI1*	*SI2*	*BI1*	*BI2*
Gender								
Male	3.2	4.2	4.2	3.1	3.3	2.9	3.9	3.6
Female	3.6*	4.2	4.1	3.8*	3.7	3.1	4.0	3.8
Degree								
Bachelor	3.4	4.2	4.1	3.5	3.4	3.0	4.0	3.8
Masters	3.4	4.2	4.2	3.6	3.1	2.8	4.0	3.5
PhD	3.8	4.1	4.0	3.4	3.0	2.6	3.4*	3.6
Faculty								
Math-Mechanic	3.3	4.2	4.2	3.5	3.4	3.0	3.9	3.6
Applied Mathematics	3.4	4.2	4.1	3.5	3.3	3.0	3.9	3.9

* p-value < 0.05

3.4.3 Adoption of IoT Services

Results of the analysis show that the strongest predictor of students' intentions to use IoT services is effort expectancy (EE). Perceived benefit of using IoT services for educational purposes (PE1) and social influence by peers (SI1) have smaller influence on behavioral intentions to use IoT services, while no significant influence of increased chances to get a better job (P1) was found.

Students' intentions to adopt IoT services after graduation are mainly affected by social influence by instructors and peers, as well as, by better understanding of course materials. Besides that, effort expectancy has small predictive power for students' behavioral intentions to use IoT services after graduation.

Interestingly, social influence by peers (SI1) significant influence on students' perceived benefit of using IoT services for educational purposes (PE1), while social influence by university instructors' (SI2) affects students' beliefs that usage of IoT services can increase their chances to get a better job (PE2).

Table 24 shows average values of model's items related to adoption of Internet of Things services across different groups of respondents.

Table 24: Analysis of Averages across Groups for IoT Adoption

Factor	*Performance expectancy*		*Effort expectancy*		*Social influence*		*Behavior intention*	
	PE1	*PE2*	*EE1*	*EE2*	*SI1*	*SI2*	*BI1*	*BI2*
Gender								
Male	2.9	3.4	4.1	3.5	2.8	2.4	3.7	3.0
Female	3.0	3.6	4.0	3.9*	2.8	2.7	3.7	3.0
Degree								
Bachelor	2.9	3.6	4.0	3.6	2.9	2.6	3.7	3.0
Masters	2.7	3.3	4.2	3.9	2.3*	2.5	3.6	3.0
PhD	3.3	3.5	4.1	3.9	2.9	2.3	3.7	3.2
Faculty								
Math-Mechanic	2.9	3.4	4.0	3.7	2.9	2.5	3.7	3.0
Applied Mathematics	3.0	3.6	4.0	3.6	2.7	2.6	3.6	3.0

* p-value < 0.05

Analysis of means using independent T-tests and one-way ANOVA shows females have greater average effort expectancy than males, so they believe more strongly that they can become proficient at using IoT services. Besides than, masters students, in average, experience lower social influence by peers to use IoT services than BA and PhD students do.

3.4.4 Adoption of PaaS

Analysis of the survey results related to PaaS adoption shows that the strongest effect on behavioral intention to adopt PaaS in near future has perceived increase in productivity (PE1, 40%), while the effort expectancy is the second strongest predictor (EE1, 28%). Social influence by peers (SI1) and university instructors (SI2), as well as, students' beliefs that usage of PaaS services can increase their chances to get a better job (PE2) also have some influence on students' behavioral intentions.

Students' intentions to adopt PaaS after graduation are primarily influenced by perceived increase in productivity (PE1), students' beliefs that usage of PaaS services can increase their chances to get a better job (PE2), and social influence by peers (SI1) and university instructors (SI2). Effort expectancy also have some influence on students' behavioral intentions.

Moreover, analysis shows that there is a strong correlation between social influence by peers (SI1) and instructors (SI2) and performance expectancy (PE1 and PE2).

Table 25: Analysis of Averages across Groups for PaaS Adoption

Factor	*Performance expectancy*		*Effort expectancy*		*Social influence*		*Behavior intention*	
	PE1	*PE2*	*EE1*	*EE2*	*SI1*	*SI2*	*BI1*	*BI2*
Gender								
Male	2.7	3.5	3.7	3.3	2.7	2.4	3.3	3.2
Female	2.9	3.6	3.6	3.5	2.6	2.6	3.2	3.0
Degree								
Bachelor	2.8	3.6	3.7	3.4	2.8	2.6	3.3	3.2
Masters	2.6	3.6	3.6	3.3	2.4	2.4	3.1	2.9
PhD	2.9	3.3	3.4	2.9	2.8	2.3	2.8	2.8
Faculty								
Math-Mechanic	2.8	3.6	3.8	3.4	2.7	2.4	3.3	3.2
Applied Mathematics	2.8	3.6	3.6	3.4	2.7	2.6	3.1	3.0

Analysis of means using independent T-tests and one-way ANOVA shows that there is no significant differences in averages of model's items related to PaaS adoption across different groups of respondents.

3.4.5 Adoption of IBM Bluemix

Overall, analysis of survey results with help of IBM Watson predictive analytics demonstrates that students' behavioral intentions to adopt emerging technologies discussed in this master's thesis are primarily affected by all three factors included on theoretical model, namely, performance expectancy, effort expectancy, and social influence. Besides that, relationships between social influence and perceived usefulness was found for all technologies in question.

Finally, the influence of students' intentions to adopt cognitive computing, advanced analytics, IoT, and PaaS on behavioral intention to use IBM Bluemix platform was analyzed. Predictive strengths of relationships can be found in Table 26.

Table 26: Predictive Strength of Drivers of Bluemix Adoption (in percent)

Technology	***Cognitive computing***		***Advanced analytics***		***Internet of Things***		***PaaS***	
	BI1	*BI2*	*BI1*	*BI2*	*BI1*	*BI2*	*BI1*	*BI2*
Predictive strength	66	64	59	61	61	-	71	66

As it is shown in the Table 26, the strongest predictors of Bluemix adoption are student's intention to adopt PaaS (predictive strength: 66-71%) and cognitive computing services (predictive strength: 64-66%), while intentions to use advanced analytics also significantly affect intentions to use IBM Bluemix computing platform. As for the IoT services, only whose students who are interested to use these tools for educational purposes are likely to adopt IBM Bluemix.

Interestingly, a much smaller percentage of PhD students than percentage of BA and MS students participating in the survey report behavioral intentions to use IBM Bluemix in future. Besides that, according to the survey results, females are slightly more interested to try IBM Bluemix platform.

CONCLUSION

The current research is devoted to the factors affecting adoption of digital computing platforms and top emerging technologies offered by these platforms, namely, cognitive computing, cloud computing, Internet of Things, and advanced analytics among university students. Hence, four research questions related to the predictors of students' behavior intentions to use these technologies were formulated.

In order to answer to the research questions, a multidimensional implementation of modified UTAUT model was applied. According to the model, students' intentions to use each of four technologies in question are influenced by three predictors: performance expectancy, effort expectancy, and social influence. Furthermore, students' intentions to use digital computing platforms are theorized to be influenced by students' intentions to use services and technologies offered by these platforms. In total, sixteen research hypotheses were formulated.

The formulated research hypotheses were tested using structural equation modeling approach with data received from the questionnaires which were distributed among bachelor, masters, and PhD students studying at faculty of mathematics and mechanics and faculty of applied mathematics and control processes of Saint Petersburg University (overall, 150 students participated in the survey). Besides that, relationships between the model's items were also explored using IBM Watson predictive analytics.

Summary of Results

The research results have revealed several interesting findings. The following section includes answers to the research question formulated in the first chapter.

Adoption of Digital Computing Platforms

Overall, 56.2 percent (82 people) of students participating in the survey claimed that would be interested to participate in IBM Academic Initiative and try IBM Bluemix platform. However, only a few students reported that they had had a prior experience with IBM Bluemix, which shows a low level of SPbU IT students' awareness about the platform.

Results of the SEM analysis show that students' intentions to adopt digital computing platform IBM Bluemix in the future are influenced by their intentions to use cognitive computing services and platform-as-a-service. This means that the students who are willing to use cognitive computing technologies such as natural language processing, computer vision, and neural networks for development of software applications are more likely to adopt a digital computing platform in order to quickly and economically access these technologies.

Interestingly, data analysis with Watson analytics revealed that students' intention to use advanced analytics tools can also be a predictor of intentions to use a computing platform, but this relationship is strong only for those students who are interested in using advanced analytics for educational purposes. However, no statistical evidence was found in support of a link between students' intentions to use advanced analytics after graduation and intentions to use digital computing platforms offering advanced analytics services. This means that the students, who think that they will need to use advanced analytics at a future job, believe that they will use some standalone analytics tools (for example, QlikView and Splunk) rather than digital platforms offering advanced analytics services along with many others.

Finally, no statistically significant link between students' intentions to use internet of things services and intentions to use digital computing platform was discovered, that is students willing to develop IoT-related applications are not likely to use internet of things services offered by digital computing platforms. It can be described by the fact that most of IoT applications developed by university students do not require advanced technologies and services (i.e., device orchestration, security, advanced analytics, real-time monitoring) provided by major computing platforms, though they can be useful for complex IoT projects.

Factors Influencing Adoption of Cognitive Computing Services

Research question 1: Which factors affect adoption of cognitive computing services among university students?

Answer to the research question 1: The students' intentions to adopt cognitive computing services are directly affected by performance expectancy and effort expectancy, and indirectly affected by social influence by university staff and peers.

The results of the empirical study show that performance expectancy and effort expectancy are significant predictors of students' intentions to adopt cognitive computing services technology, which is consistent with previous studies devoted to the adoption of technologies in the university settings. This means that the students, who believe that they can easily learn how to use cognitive computing technologies and that knowledge of these technologies can be useful for educational and professional purposes, are more likely to adopt these technologies in the future.

Hence, in order to promote the adoption of cognitive computing services among university students, it is necessary to persuade them that knowledge of these technologies can be beneficial for them while these technologies can be learned with a reasonable amount of efforts.

Besides that, analysis with IBM Watson analytics revealed an indirect effect of social influence on behavioral intentions. The students who are influenced by instructors to use cognitive computing technologies perceive these technologies as more useful, while students who experience social influence from peers perceive cognitive computing technologies as more easy to use.

Therefore, informing the students by university staff about benefits of familiarity with cognitive computing technologies can increase students' perceived benefit of using these technologies, which, in turn, drives their adoption. Furthermore, increased knowledge exchange about cognitive technologies among students can increase a perceived effortlessness of using these technologies, which also leads to the increased level of adoption.

In addition, interestingly, effort expectancy has stronger influence on intentions to use computing technologies for females than for males, so it is more important for females to have good learning materials on how to use cognitive computing services.

Adoption of Internet of Things Services

<u>Research question 2:</u> Which factors affect adoption of Internet of Things services by university students?

<u>Answer to the research question 2:</u> Acceptance of Internet of Things services by university students is influenced by effort expectancy and social influence from peers and university staff.

The study results show that effort expectancy and social influence significantly affect students' behavior intentions to adopt Internet of Things services. This means that the majority of students think internet of things services should be easy to use. In other words, if students feel that the internet of things services could be easily learned and used, their willingness to employ them will be enhanced. Besides that, the influence of effort expectancy on behavioral intentions is stronger for females than for males.

Hence, in order to promote adoption of the IoT services among university students, they should be persuaded by peers and university staff that they could learn how to develop software applications using IoT with a reasonable amount of efforts. However, unlike other technologies discussed in this paper, IoT projects require not only software development skills, but also knowledge and experience with electronic circuits and hardware. Lack of such skills can be a serious barrier for adoption of IoT services among university students.

Besides that, survey results show that, in average, students do not experience substantial social influence to use IoT services from peers and university instructors which also leads to the low level of technology adoption.

The lack of statistically significant relationship between perceived usefulness and students' behavioral intentions can be described by the fact that only a small fraction of respondents had any prior experience with Internet of Things. The previous technology adoption studies (Castaneda, Munoz-Leiva, & Luque 2007) showed that inexperienced users, in most cases, care more about the ease of use of new technology than of its benefits.

Adoption of Platform-As-a-Service

Research question 3: Which factors affect adoption of Platform-as-a-Service by university students?

Answer to the research question 3: Adoption of Platform-as-a-Service among university students is affected by performance expectancy and effort expectancy. Social influence also have indirect effect on students' behavioral intentions through performance expectancy.

The results of the study demonstrate that performance expectancy was the most significant factor behind the students' attitude toward using PaaS. It is therefore believed that a student with higher performance expectancy of PaaS is more likely to try these technologies. Besides that, analysis shows that there is a link between social influence and performance expectancy.

Hence, in order to increase adoption of PaaS in university, students should be persuaded that experience with PaaS could increase their academic results or help them to get a better job after graduation.

However, analysis of averages show that now students have low values for performance expectancy, it means that students do not really believe that usage of PaaS can be beneficial for them during studying at the university. It might be due to the fact that, typically, students do not participate in complex projects where usage of PaaS can be economically justified.

The second significant predictor of PaaS adoption is effort expectancy, that is, the easier it is for a student to become skillful at using platform-as-a-service, the more likely he or she will use it in future. Besides that, there is a stronger relationship between effort expectancy and behavioral intentions for females than for males.

Adoption of Advanced Analytics Services

Research question 4: Which factors affect adoption of advanced analytics by university students?

Answer to the research question 4: The students' intentions to use advanced analytics tools are primarily influenced by social influence and performance expectancy, while no statistical evidence was found in support of link between effort expectancy and behavioral intentions to adopt advanced analytics tools.

The strongest predictor of university students' intentions to use advanced analytics tools is social influence. It means that whose students who experience greater social influence by university staff and peers are more likely to adopt advanced analytics services.

Another significant predictor of behavioral intentions to adopt advanced analytics is performance expectancy, that is, the students who believe that knowledge of advanced analytics tools can be useful for their studying at the university or future job have greater intentions to use these tools in future. This shows that students attach some importance to the advantages brought forward by advanced analytics tools, such as simple data retrieval and refinement process, integrations with third-party data sources, insights and recommendations, big data analytics, rich visualization tools, collaborative work and so on.

Besides that, detailed analysis of relationships between the model's items with help of Watson Analytics shows that there is a correlation between perceived influence by university instructors and perceived benefit of using advanced analytics services. Hence, in order to increase adoption of these services in educational context, university instructors should inform and persuade students that proficiency with advanced analytics services can increase their academic results and better prepare for the future job.

The non-significance of the relationship between perceived ease of use and students' acceptance intentions can be described by the fact that majority of students assume that advanced analytics tools are much easier to use than traditional data analysis tools used in universities, such as IBM SPSS, MATLAB, or R.

In addition, doctoral students have significantly lower intentions to use advanced analytics tools during studying at the university. A plausible explanation for this outcome is that it might be difficult to justify the usage of advanced analytics tools for scientific research; therefore, it is not an appropriate tool for doctoral students.

Theoretical Implications

Research makes several theoretical contributions to the technology adoption literature.

First, to the best of our knowledge, no earlier studies have used a multi-dimensional implementation of any technology adoption model in order to investigate factors affecting adoption of digital computing platforms which offer a bundle of technologies in one place. This study applied a multi-dimensional implementation of the modified UTAUT model where behavioral intention to adopt a computing platform IBM Bluemix is theorized to be affected by behavioral intentions to adopt four emerging technologies included in IBM Bluemix platform: cognitive computing, advanced analytics, internet of things, and platform-as-a-service. Potentially, the same approach could be used for investigation of factors influencing adoption of other platforms which offer various digital services.

Second, the developed model for adoption of platform-as-a-service (PaaS) may contribute to the cloud computing adoption literature. Previously, much attention has been given to the adoption of software-as-a-service (SaaS) solutions, but little attention was paid by researchers to the factors affecting adoption of platform-as-a-service and infrastructure-as-a-service (IaaS). The current research shows that that PaaS adoption is affected by performance expectancy and effort expectancy, which is consistent with previous studies devoted to the adoption of SaaS.

Third, unlike previous studies of factors influencing adoption of IoT services and advanced analytics tools, this study has theoretically contributed to the literature by examining the effects of the model's constructs in university settings. The research findings demonstrate that in university context, which is characterized by low experience of students and high social influence of university instructors, some relationships between theoretical model's items can be insignificant, because for inexperienced users ease of use of new technologies is more important than their usefulness, while for users who have solid experience with related technologies perceived usefulness is more important that perceived ease of use. This finding corresponds with previous researches (Huang 2016) devoted to the adoption of cloud computing in universities.

Besides that, the research findings suggest that social factors have direct and indirect effect on students' intentions to adopt new technologies. For all technologies analyzed in this study, social influence by university instructors and peers influenced students' perceived benefit and perceived ease of use of new technologies, which, in turn, influence students' attitude towards adoption of these technologies.

Moreover, the results show that there is a significant gender differences in terms of the effects of the effort expectancy on students' behavioral intention. It was found that effort expectancy is a stronger determinant of adoption intentions for women than for men. However, no statistical evidence in support of moderating effect of student's academic degree on relationships between variables was found.

Finally, this study used advanced analytics tool "IBM Watson analytics" in order to investigate factors affecting technology adoption, while most of the previous works on the topic of technology adoption used traditional statistical models in order to test hypotheses about relationships between theoretical model's constructs. Overall, results from analysis with IBM Watson analytics are consistent with results from analysis with structural equation modeling approach. However, IBM Watson analytics helps to identify indirect relationships between model's items more easily because it allows exploring hidden relationships in input data by using simple yet powerful visualization.

Managerial Implications

Beyond the theoretical implications, this study also has practical implications drawn from the research findings.

The study revealed that only intentions to use cognitive computing services and platform-as-a-service drive students' intentions to adopt IBM Bluemix platform. Thus, in order to promote adoption of IBM Bluemix among university students, the platform provider should concentrate its marketing efforts on informing students about benefits of adopting cognitive computing services and PaaS for their productivity, educational performance, and future employment.

Besides that, the study results showed that IT students not only expect useful services, but also expect to become proficient at usage of these services with a reasonable amount of efforts and time spent. Since effort expectancy has greater influence for inexperience users, technology vendors should provide learning materials in various forms (guides, documentation, video lectures, presentations, webinars, and online courses) in order to introduce new technologies to students more smoothly.

Since perceived ease of use of technologies is more important for females than for males, female students should be provided with additional learning materials. For example, they should be provided with greater amount of educational newsletters sent by email after registration, and "getting started" online tour for females should include more information relevant for them.

In addition, to decrease a perceived difficulty of new technologies and promote adoption of IoT services among students, interdisciplinary groups of students with various educational backgrounds (software development, electrical engineering, science etc.) could be organized so students would not be afraid that they lack some crucial skills necessary for IoT projects.

Moreover, marketers should not overlook the effect of the social influences on students' acceptance of the discussed technologies. Since social influence by peers and university instructors significantly affects students' perceived benefit and ease of use, it is crucial that these people persistently encourage students to use services provided by digital computing platforms. Hence, it is essential for vendors to inform university instructors about new services and tools offered by platforms and motivate them to introduce these tools to the students by explaining their benefits, demonstrating use, and persuading students to use these tools for projects.

Furthermore, in order to increase technology adoption among university students, vendors need to identify innovators and early adopters and stimulate their usage of technologies, so that they could use their social influence to encourage peers and serve as a reference for facilitating the process of technology diffusion in the future. Such events as hackathons and workshops devoted to the new technologies can be useful in identification of potential early adopters of new technologies.

Limitations and Future Research

Although proper research procedures were applied, the research has a number of limitations which should be identified and addressed in future studies. Following are the description of limitations of the empirical research which must be taken into consideration.

First, the sample is limited to the students of Saint Petersburg State University, so results may be not generalizable, because adoption factors for students from other universities might be different and the findings may not apply to students from less advanced universities.

Besides that, the sampling method has potential bias because a convenience sampling method was used. To achieve a greater generalizability of the findings, future researchers should randomize their sample.

In addition, while the sample of 150 students met minimum requirements for the analysis, some results might still be non-significant due to a relatively small sample size. Further studies with greater sample size are recommended in order to provide results that are more accurate.

Furthermore, results of the research could be affected by self-selection bias, as respondents who are less familiar with technologies in question, may be not able to answer the survey questions.

Moreover, the research design was cross-sectional rather than longitudinal, but cross-sectional studies do not provide as much insight as longitudinal. Therefore, future research should adopt longitudinal research design to measure changes in respondents' perceptions and intentions over time, as well as, actual usage behavior.

Finally, future research can incorporate constructs from other technology adoption models in order to investigate how other potential constructs that may affect students' perceptions of performance expectancy and increase a predictive power of the research model.

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Appendix 1. Descriptive statistic

Measure	*Mean*	*Median*	*Mode*	*Variance*	*SD*	*Skewness*	*Kurtosis*
CC_EE1	4,05	4,00	4,00	0,61	0,78	-0,42	-0,40
CC_BI1	3,60	4,00	3,00	1,14	1,07	-0,29	-0,52
CC_EE2	3,61	4,00	3,00	1,18	1,09	-0,26	-0,86
CC_SI1	2,57	3,00	3,00	1,28	1,13	0,32	-0,38
CC_PE1	3,27	3,00	3,00	0,99	1,00	-0,04	-0,26
CC_PE2	3,88	4,00	5,00	1,07	1,04	-0,56	-0,41
CC_SI2	2,52	3,00	3,00	1,38	1,17	0,34	-0,55
CC_BI2	3,20	3,00	3,00	1,35	1,16	-0,11	-0,79
AN_EE1	4,14	4,00	4,00	0,68	0,83	-1,14	1,99
AN_BI1	3,95	4,00	4,00	1,02	1,01	-0,88	0,38
AN_EE2	3,47	4,00	4,00	1,12	1,06	-0,52	-0,24
AN_SI1	3,35	3,00	4,00	1,09	1,04	-0,42	-0,25
AN_PE1	3,39	3,00	4,00	1,15	1,07	-0,29	-0,54
AN_PE2	4,18	4,00	5,00	0,90	0,95	-1,12	0,80
AN_SI2	2,99	3,00	3,00	1,46	1,21	0,12	-0,86
AN_BI2	3,68	4,00	4,00	1,18	1,09	-0,59	-0,28
IOT_EE1	4,05	4,00	5,00	0,91	0,95	-0,84	0,26
IOT_BI1	3,72	4,00	5,00	1,26	1,12	-0,52	-0,59
IOT_EE1	3,65	4,00	4,00	1,20	1,09	-0,50	-0,51
IOT_SI1	2,77	3,00	3,00	1,11	1,05	0,23	-0,34
IOT_PE1	2,93	3,00	3,00	1,37	1,17	0,02	-0,76
IOT_PE2	3,49	4,00	4,00	1,28	1,13	-0,56	-0,20
IOT_SI2	2,55	3,00	3,00	1,15	1,07	0,27	-0,42
IOT_BI2	3,03	3,00	3,00	1,42	1,19	0,01	-0,90
PAAS_EE1	3,68	4,00	4,00	0,85	0,92	-0,25	-0,29
PAAS_BI1	3,24	3,00	3,00	1,28	1,13	-0,09	-0,80
PAAS_EE2	3,37	4,00	4,00	1,11	1,05	-0,47	-0,29
PAAS_SI2	2,68	3,00	3,00	1,14	1,07	0,07	-0,52
PAAS_PE1	2,78	3,00	3,00	0,90	0,95	-0,21	-0,12
PAAS_PE2	3,61	4,00	4,00	1,13	1,06	-0,48	-0,40
PAAS_SI2	2,49	2,50	3,00	1,07	1,04	0,22	-0,56
PAAS_BI2	3,11	3,00	4,00	1,23	1,11	-0,02	-0,88